CRANFIELD UNIVERSITY

VIRGINIA JIMENEZ-DONAIRE

ON-LINE MEASUREMENT OF SELECTED SOIL PROPERTIES TOWARDS THE REFINEMENT OF NITROGEN FERTILISATION MANANGEMENT ON VEGETABLE CROPS

SCHOOL OF ENERGY, ENVIRONMENT AND AGRIFOOD
Cranfield Soil & Agrifood Institute

MPhil
Academic Year: 2012 - 2015

Supervisor: Dr. Abdul M. Mouazen
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ABSTRACT

Fertiliser applications in vegetable crops are one of the main input costs of production. Thematic soil maps have been widely used for decades to characterise soil nutrients and, therefore, apply variable rate fertilisers. However, traditional variable rate methods used in soil sampling are time-consuming, costly and not accurate. Thus, they fail in providing a true estimate of the nutrients soil needs. To obtain better crop response to inputs, a rapid, non-destructive, timely and cost-effective soil analysis are needed to enable site-specific fertiliser applications. Proximal soil sensing with visible and near infrared (vis-NIR) spectroscopy is a promising tool to assist in variable rate applications. This thesis aims to develop reliable calibration models for a previously developed on-line visible (vis) and near infrared (NIR) spectroscopy sensor (Mouazen, 2006), for the prediction of soil properties in vegetable crop fields for a better N fertiliser management. Experiments were established in crops of cauliflower (*Brassica oleracea*) during 2013 season (two fields) and 2014 season (three fields), in UK. A mobile, fibre-type, vis–NIR spectrophotometer (AgroSpec, Tec5 Technology for Spectroscopy, Germany) with a measurement range of 305-2200 nm was used to measure soil spectra in diffuse reflectance mode, measuring up to ~1500 points per ha. Four different calibration sets were tested to establish the most accurate calibration model for moisture content (MC), soil organic carbon (OC), pH and total nitrogen (TN), using partial least squares (PLS) regression analysis selected according to different spectral library size and geographical scale: Scenario 1 (SC1 (local)), Scenario 2 (SC2 (regional)), Scenario 3 (SC3 (national)), Scenario 4 (SC4 (continental)). The best results in cross-validation were obtained for MC with SC2 (R^2 = 0.89; RPD > 2.5), followed by SC4 (R^2 = 0.88; RPD = 2.91-3.31, in 2013 and 2014, respectively); and SC1 and SC4 worked very well for MC on-line prediction (R^2 > 0.90 and RPD > 2.5). SC3 and SC4 both provided the best performance for OC and TN in cross-validation, whereas no clear trend was observed for on-line prediction. Poor model performance was obtained for pH in on-line predictions (R^2 < 0.30 and RPD < 0.9). Although the calibration models using the on-line vis-NIR sensor provided good and detailed information of the

soil nutrients analysed, future research will be needed to estimate these properties more accurately, with the aim to develop reliable vis-NIR calibration models for the on-line measurement in vegetable crop fields.

Keywords:

Vis-NIR spectroscopy, horticulture, on-line measurement, nitrogen fertilizer, variable-rate.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

CV	Coefficient of variation
DEFRA	Department for environment food and rural affairs
DGPS	Differential global positioning system
DSS	Decision support system
EC	Electrical conductivity
GIS	Geographic information system
IDW	Inverse distance weighting
MZ	Management zone
MIR	Mid infrared
NDVI	Normalised difference vegetation index
NIR	Near infrared
PA	Precision Agriculture
PLSR	Partial least square regression
R^2	Coefficient of determination
r	Coefficient of correlation
MC	Moisture content
OC	Organic carbon
RB209	Fertiliser manual for agricultural and horticultural crops
RMSEP	Root mean square error of prediction
RPD	Residual prediction deviation
SD	Standard deviation
SOM	Soil organic matter
SSCM	Site specific crop management
TN	Total nitrogen
UAV	Unmanned aerial vehicles
UR	Uniform rate
USDA	United States department of agriculture
VR	Variable rate
vis	Visible

CHAPTER 1. INTRODUCTION

World population has increased considerably since the second half of the 20th century and food demand has risen even faster. Thanks to the research, development and other technological advances occurring between the 1940s and the late 1960s, production of the limited or even decreasing land is enhanced by intensification, which led to food supplies increase faster than demand (Southgate, 2009). However, a greater support for technological improvement is still necessary to avoid food scarcity in the future. Today many technology improvements in agriculture might be attributed to Precision Agriculture (PA) (also called precision farming or site-specific management of resources). PA can be defined as an agricultural philosophy that improves farm management throughout reducing inputs (such as seed, fertilisers, pesticides, water, planting, and tillage) having in mind soil and crop variability, and increasing outputs (improving profitability and quality/quantity of production); while minimising impacts on the environment (Whelan and McBratney, 2000; Kuang, 2012). Some authors declare that the aim of PA is to give answers for field management on a more precise fine-scale (site-specific) agriculture production, which includes variability in space and time. The true practical applicability of PA technologies will remain linked to high-tech and digital agriculture, including the global positioning system (GPS) for position coordinates, geographic information system (GIS) for yield mapping, remote sensors and proximal sensors, and variable rate (VR) technologies (Stafford, 2000). Moreover, to provide better information related to data on crop, soil and environmental factors a further agricultural technology is required, particularly in the area of sensing and mapping systems (Robert, 2000).

On-line soil sensors are classified under proximal soil sensors, which refer to those sensing technologies used to collect data while moving across the landscape. Visible (vis) and near infrared (NIR) spectroscopy technology has the potential to provide a rapid, non-destructive, timely, low-cost and, sometimes, more accurate soil analysis enabling within-field variability to be identified (Viscarra-Rossel et al., 2006). This optical technique is suitable for laboratory, *in situ* and on-line measurement conditions. On the other hand, traditional laboratory analysis methods are time-consuming, costly and less accurate. Generally, visible and near infrared (vis-NIR) spectroscopy has proven to be a good tool for the prediction of some soil properties (Thomasson et al., 2001; Dunn et al., 2002; Kuang et al., 2013), since they can provide quantitative measurement of multiple properties, simultaneously. Some studies have focused on creating robust vis-NIR calibration models for better accuracy of soil properties prediction. Several works on the performance of vis-NIR calibration models in relation with geographical scale were carried out (Kuang and Mouazen, 2011; Guerrero et al., 2014). Some authors reported a good performance of models developed with one field sample (Christy, 2008; Mouazen et al., 2006). Mouazen et al. (2006) showed that prediction of MC at a field scale was better than that with samples collected from several fields across Belgium and Northern France. So far, the effect of sample variability linked with geographical scale on model prediction accuracy for on-line measurement was not tested, particularly in fields with vegetable crop production system.

In this study, a robust and reliable fibre-type vis-NIR spectroscopy sensor (Mouazen, 2006) for on-line measurement was used in several fields with vegetable crop production. The aim was to refine nitrogen fertiliser applications in vegetable crop production fields by acquiring high-resolution data to inform VR nitrogen fertilisation for increasing yield and improving yield quality at reduced input cost. In order to achieve this aim, the performance on the on-line vis-NIR sensor was optimised by compare the performance and accuracy of calibration models developed for OC, TN, MC, and pH for individual farms with that of general models at regional, national and continental scales.

CHAPTER 2. LITERATURE REVIEW

Precision horticulture (PH) is the application of PA in specialty crops. Specialty crops are defined in the USDA (http://www.ams.usda.gov/AMSv1.0/scbgpdefinitions) as fruit and vegetables, tree nuts, dried fruits, horticulture and nursery crops (including floriculture) (Lee et al., 2010). Sensors for the measurement of properties and characteristics for specialty crops are critical for monitoring and controlling product quality and safety (Ruiz-Altisent et al., 2010). Sensors play an important role in identifying product properties. This review focuses on investigating the following two points:

- Use of automation / precision agronomy in horticulture
- Improved monitoring techniques in horticulture

2.1 Detection of canopy characteristics

Crop canopy volume or biomass is an important factor for precise fertiliser application, irrigation, chemical applications, as well as health assessment (Smart et al., 1990; Haselgrove et al., 2000; Wood et al., 2003). It is directly related to crop yield for many horticultural crops including trees. Smart et al. (1990) described the relationship between canopy management and yield for grape. Haselgrove et al. (2000) discussed light exposure and phenolic compounds of berries in different canopy conditions. Wood et al. (2003) investigated the relationship between pistachio nut fruit ripening date late season canopy retention. Fernández-Pacheco et al. (2014) successfully applied and validated the use of digital photography to calculate the crop coefficient in lettuce to improve water consumption and fertiliser application in the crop. One of the ultimate goals of estimating canopy volume is site specific variable rate application of fertiliser and pesticides (Giles et al., 1989; Molto et al., 2001; Solanelles et al., 2006; Gil et al., 2007). For example, Zaman et al. (2005) generated a prescription map for variable nitrogen application to citrus trees from the measurements of tree sizes by the ultrasonic system, and reported that 38–40% of granular fertilizers were saved when variable nitrogen applications were implemented on a single tree bases. Van Evert et al. (2013) showed the potential of a canopy sensor (Crop Circle, the Netherlands) reflectance to determine sidedress nitrogen fertilisation rate in potato. They concluded that the canopy sensor is ready for practical use of nitrogen fertilisation. However, authors ignored the actual nitrogen content in the soil, assuming that the crop canopy will reflect the nitrogen status in the plants.

There have been several attempts for canopy volume assessment, utilizing different methods such as ultrasonic, laser scanning, aerial sensing, and light penetration measurement of the canopy. Besides those methods, satellite imagery or synthetic aperture radar (SAR) satellites were also used for crop biomass sensing. Todd et al. (1998) estimated biomass of rangelands using spectral indices from the LANDSAT TM imageries. They studied the use of green vegetation index (GVI), brightness index (BI), and wetness index (WI), the normalized difference vegetation index (NDVI) and the red waveband (RED) in the estimation of biomass content of ungrazed and grazed grasslands.

2.1.1 Laser scanning

Wei and Salyani (2004) applied a laser scanning system (AccuRange AR4000–LIR, Acuity Research Inc., Menlo Park, Cal.) to measure citrus tree height, width, and canopy volume. They reported that the system showed good repeatability with measurement errors less than 5%. This type of canopy characteristics study is important in the development of tree specific or site specific management practices. Further, Wei and Salyani (2005) implemented a laser scanning system to measure the foliage density of a citrus canopy. When compared with manually collected data, the results showed an overall correlation of R^2 = 0.96 with an RMSE = 6.1%. The laser measurements showed a good repeatability with an average coefficient of variation (CV) of less than 3%. This shows that this technique has high potential in horticulture applications, although it has not been fully explored so far. Tagarakis et al. (2012) measured several canopy properties (canopy development, flowering, berry set, veraison, and harvest) on vineyards using a Crop Circle sensor. They reported all the measurements taken were highly similar with yield and quality index (> 70 % degree of agreement). Recently, Tagarakis et al. (2013) used a laser scanner to map pruning wood in vineyards. Authors reported that the laser scanner can be successfully used to map within-field variability in vine performance. Selbeck and Pforte (2013) have combined an NIR imagery system with a laser scanner to determine palm tree canopy cover, arriving at *r* values between automated and manual reference measurements of 0.70 to 0.87. A strong correlation between the NIR imagery and laser scanner was observed with an *r* value of 0.92.

2.1.2 Ultrasonic sensing

Ultrasonic sensors were used in crop production starting the late 1980s. Giles et al. (1988) used commercial ultrasonic range transducers to measure tree canopy volume, reporting an error rate of less than 2% on calibration targets and an average error of 10% for apple and peach orchards application. Then, Giles et al. (1989) investigated spray volume savings using an ultrasonic measurement which ranged between 28 and 52%, and varied greatly depending on target crop structure. Molto et al. (2001) also investigated the possibility of saving the chemicals by measuring the distance between the sprayer and tree canopy using ultrasonic sensors and reported savings of spraying products up to 37%. Other similar studies also reported chemical saving in spraying operations. Schumann et al. (2005) investigated the performance of a commercial variable rate spreader in a commercial citrus grove, based on ultrasonically measured tree size in Brazil orchids. The concluded that the spreader design was not suitable for rapid fertilisation rate changes between single tree spaces. They proposed that this performance can be greatly improved by substituting its hydraulic servo control valves with faster devices. Solanelles et al. (2006) tested a prototype sprayer with an electronic control system containing ultrasonic sensors in olive, pear and apple orchards, and reported 28–70% sprays product savings when comparing spray deposits to a conventional application. Gil et al. (2007) also reported an average of 58% less liquid applied using ultrasonic sensors when comparing a uniform application rate with variable rate of a sprayer based on vineyard structure variations. Balsari et al. (2002) developed a prototype sprayer which could measure target size and density of apple trees using ultrasonic sensors and found that travel speed did not significantly affect the vegetation measurement using the sensor, and suggested that an average of at least 10 measurements in every meter of travel distance would be needed for proper adjustment of the sprayer.

2.1.3 Light penetration/reflectance-based measurement

Light penetration has been used to measure the trees density. Studies showed that the light penetration was a nonlinear measurement of the leaf density. Jahn (1979) used the radiation measurement as a mean of estimating canopy density. The trees under study were defoliated at different levels to obtain their radiation penetration. The tree size was used to determine the leaf area index (LAI) and the leaf area to canopy area ratios (LAC). Results showed that the penetration of photo synthetically active radiation (PAR) increased in a curvilinear fashion as defoliation increased and LAC decreased. However, other researchers used light reflectance from broccoli plants to determine the N demand using a digital, light-sensitive (ISO 200-2400, spectral range 250-1300 nm), high spatial resolution imager (S1 PRO, Leica, Germany) (Pfenning et al. 2007). Yang et al. (2011) implemented successfully the vis-NIR spectroscopy for *in situ* measurement of tomato growing stage and the harvest time.

2.1.4 Thermography to measure plant water stress

Thermography can be used to measure canopy temperature. Similarly to visible (RGB) or NIR images, thermal images contain spatial information about the imaged objects. Thermal imaging plays a major role in mapping of crop water status, detection and mapping of crop diseases and detection of fruits in tree canopies. However, canopy temperature alone, cannot be an absolute indicator of water stress since it is affected by the meteorological conditions at the time of measurement. An index that normalizes these conditions was suggested, the ‘Crop Water Stress Index’, CWSI (Idso et al., 1981). CWSI is based on the difference between canopy temperature, as measured by infrared thermometry (IRT), and that of a ‘non water-stressed baseline’ referring to the temperature of well watered crop. Due to their complementary nature, combination of visible

RGB, NIR and TIR images can provide additional information. Thermal, in conjunction with visible and NIR images enable exclusion of non-leaf material in the estimate of canopy temperature and the possibility of selecting specific parts of the canopy for water stress estimation (Moeller et al., 2007; Leinonen and Jones, 2004; Alchanatis et al., 2006). Very recent study reported on the successful use of a thermal imagery combined with a crop water stress index for in seasonal irrigation management in potato fields (Rud et al, 2013). Kaukoranta et al. (2005) used infrared thermography method to detect water deficit in a greenhouse cucumber. Author's generated indices based on temperatures of crop canopy and reference surface along row were calculated. López et al. (2012) used a thermographic camera to evaluate the variability of the emissivity values of several horticultural varieties (aubergine, courgette, pepper and cucumber, among others) by measuring leaf and water temperature.

2.1.5 Remote sensing and unmanned aerial vehicles (UAV)

It is very common to come across many studies about the use of satellite imagery to measure NDVI, particularly in arable crop production. However, fewer reports can be found in the literature about the use of remote sensing for NDVI measurement in horticulture or vegetable crop production systems (e.g. Bonilla, et al., 2013). Recently, UAV become very popular for use in different sectors, among which precision agriculture. Ballesteros et al. (2014) estimated green canopy cover (GCC) of onion and maize from aerial observations with unmanned vehicles. Afterwards, GCC and leaf area index (LAI) relationship was tested in other to describe crop growth. Matese et al. (2013) reported on the successful use of a UAV, equipped with a multi-spectral camera to measure NDVI and a non-destructive fluorescence technique for the detection of the spatial variability of grape anthocyanin content. Rey et al. (2013) used a multispectral imagery acquired from a UAV to assess the spatial variability of a Tempranillo vineyard. Jiménez-Bello et al. (2013) utilised airborne thermal imagery acquired with a UAV for the assessment of drip irrigation system in citrus fields, concluding that the system enabled the detection of failures in the irrigation delivery system.

2.1.6 LIDAR

Planas et al. (2013) reported on a successful use of a ground-based light detection and ranging (LIDAR) sensor-based systems to estimate leaf area index (LAI) in apple orchards, which take into account the structure of the orchard expressed as combination of three components: (1) canopy leaf density, (2) height of the canopy, and width of the tree. Rinaldi et al. (2013) explained the use of a LIDAR sensor for the characterisation of phonological stages of grapevine, showing high correlation between LIDAR readings and LAI. They found that the relationship between the estimated tree row volume or leaf wall area and the growth stage of the vine was significant.

2.2 Crop yield monitoring

2.2.1 High resolution remote sensing imagery

Crop yield is perhaps the most important piece of information for crop management in precision agriculture. In recent years, many PA companies and agricultural institutions have been working with PH, especially after commercial yield monitors for orchards became available. Despite the commercial availability and increased use of yield monitors, most of the harvesters are not equipped with them. To our knowledge there are still only few commercial yield monitors for most specialty crops (Zude et al., 2008; Usha and Singh, 2013). In vegetable cropping sector, yield monitoring is mostly done manually. However, yield maps derived from remote sensing imagery can be used as an alternative when yield monitor data are not available. Traditional satellite imagery has been used for yield estimation over large geographic areas, but this type of imagery has limited use for assessing the variation in yield within fields because of its coarse spatial resolution. Therefore, airborne multispectral and hyperspectral imagery and high resolution satellite imagery have been used for mapping within-field yield variability and other precision agriculture applications. Airborne multispectral imaging systems provide image data at fine spatial resolutions and at narrow spectral bands and have the real-time monitoring capability. Many researchers have evaluated the relationships between yield monitor data and airborne multispectral imagery (Senay et al., 1998; Dobermann and Ping, 2004).

Hyperspectral imagery contains tens to hundreds of narrow bands and provides additional information that multispectral data may have missed. The commercial availability of high resolution satellite sensors such as IKONOS, QuickBird, and SPOT 5 has opened up new opportunities for mapping within-field variability. Remote sensing has been used for yield estimation for various annual crops, but only limited research has been conducted on yield estimation for specialty crops such as fruit trees and vegetables. Koller and Upadhyaya (2005a, b) examined the relationships between leaf area index (LAI) and a modified NDVI for processing tomatoes and used the LAI derived from aerial images and photosynthetically active radiation (PAR) to predict tomato yield. Their results showed that although the actual and predicted yield maps did not have a very high correlation, the two maps had similar yield patterns. Ye et al. (2007) used partial least squares (PLS) regression models to predict the yields of citrus trees from their canopy features obtained from airborne hyperspectral imagery as compared with vegetation indices and multiple linear regression models. Their results showed that vegetation indices and multispectral regression models failed to predict citrus yield, but PLS models successfully predicted citrus yield with R-squared values of 0.51 to 0.90. Ye et al. (2008) also examined the relationships between particular canopy features obtained from airborne multispectral images and the fruit yields of citrus trees and they found that mature leaves in canopies were more significantly correlated with fruit yield for the current growing season, while younger leaves were more significantly correlated with fruit yield for the following growing season. Ortega et al. (2007) used satellite imagery calibrated for green vegetable index to estimate tomato yield and quality, reporting promising results. Yang et al. (2008) evaluate CIR aerial photography and field reflectance spectra for estimating cabbage physical parameters and their results show that both aerial photography and reflectance spectra can be used to extract cabbage plant growth and yield information.

2.2.2 Machine vision

Machine vision is based on digital images and tries to mimic human perception to provide information or input to systems that need it for application of site specific crop production. The most common application of machine vision is based on silicon sensors (CCD or CMOS arrays) that are sensitive to the range of 400–1000 nm. Within this group, colour machine vision is most common, because of its low price and multitude of information contained in the colour images. Colour machine vision includes three wide spectral channels (approximately 150nm FWHM), centred at the three basic colours, red (~600 nm), green (~550 nm) and blue (~450 nm). Precision agriculture in orchards considers the tree as an individual production unit. In such an approach, sensing technologies are required in order to provide information about the status of each tree, regarding the nutrients, water status, fruit load and yield. The technology for nutrients and water status detection is similar for field crops. Nevertheless, yield estimation, as well as site specific (tree specific) handling often depends on the fruit load of the tree. Therefore, much effort has been invested in automatic fruit detection and yield estimation of fruits. Some of the fruits have distinct colour differences from the foliage and make them more distinguishable (for example mature oranges, red apples) and others have colours similar to that of the tree canopy, making them more difficult to detect (for example immature oranges and green apples). Colour machine vision has been found useful for detection of Fuji apples (red in colour) in the tree canopy when the colour contrast is high (Bulanon et al., 2002). Multispectral imaging showed the potential for detecting immature green oranges (Kane and Lee, 2007). Hyperspectral imaging, along with morphological image processing was also shown to have good potential for detecting green apples in the tree canopy (Safren et al., 2007). Occlusion is an obstacle to two-dimensional machine vision recognition of fruits and plants in natural outdoor scenes. The watershed algorithm was proved to be suitable to improve the recognition of occluded fruits in a tree canopy, as well as plant leaves (Safren et al., 2007; Lee and Slaughter, 2004). Alchanatis et al. (2007) proposed a method for automatically detecting apples in hyperspectral machine vision, which allowed the yield estimation of apples on trees at different growing stages. Authors reported an overall correct detection rate of 87.0%, with an overall error rate of 14.9%. The berry size of the Vine grape size was measured by means of a computer vision, aiming at recovering the profile of each visible berry in the grape (Rabatel and Guizard, 2007).

2.2.3 Thermography

Thermal imaging has been also used for estimating the number of fruits in orchards and grooves (Stajnko et al., 2004; Wachs et al., 2009; Bulanon et al., 2008). The detection of the fruits is based on the assumption that their temperature differs significantly from the surroundings. Image processing algorithms are more effective in detecting the fruits when the contrast between fruits and surroundings is maximum. In an attempt to evaluate the best time for fruit detection, the thermal temporal variation in citrus canopy was analysed (Bulanon et al., 2008). A relatively large temperature difference between fruit and canopy occurred from the afternoon, around 16:00, until midnight. This enhanced the fruit in the thermal images and facilitated fruit detection (Bulanon et al., 2008; Stajnko et al., 2004). Bulanon et al. (2008) employed a segmentation approach using the histogram tail method, which proved to be effective in discriminating the fruit from canopy especially when the temperature difference between leaves and fruits was large. An average true positive rate of 0.70 and a false positive rate of 0.06 were achieved. Since this success rate is marginal for robotic harvesting, thermal imaging was consequently fused with additional vision systems to improve the performance. Stajnko et al. (2004) used the pseudocolour thermal image and colour image processing tools to detect the fruits. Showing high accuracy between the numbers of apples automatically detected with the number of fruits manually counted in the images. Further, fusion of multi-modal images (thermal and RGB) can enhance the detection accuracy of fruits (Bulanon et al., 2008; Wachs et al., 2009). Furthermore, field emissivity measurements of leaves show that there is useful spectral information that may be detectable by passive remote sensing in the thermal infrared (da Luz and Crowley, 2007).

2.2.4 Mechanical

Mechanical harvester based on load cell or flow rate mechanisms are the most common equipment for the measurement of crop yield, particularly in arable crops. However, these were also implemented in the horticulture sector. Arnó et al. (2005) reported on a successful measurement of grape using a Gregoire G-140 SW harvester equipped with a DGPS. Three different grape yield monitors were used to collect yield data to enable a comparison between the spatial variability of vineyard yield in European and Australian production systems (Taylor et al., 2005).

2.3 Sensor network for agriculture and field monitoring

A wireless sensor network consists of distributed sensor nodes, which contain sensors and a wireless communication device. Sensor networks are able to collect high-resolution data at farms in real time. The use of sensor network in vegetable crop production and horticulture is less documented than that of arable crop production systems. Oki et al. (2009) developed an integrated agricultural monitoring system based on the use of high-spatial-resolution remote sensing imagery and data on sensor networks in a cabbage farm. It can produce cabbage coverage maps that provide information on cabbage growth that could be used for agricultural land management, particularly with regard to the application of fertilizer and forecasting of crop production. In Murcia (Spain), a wireless sensor network was developed and deployed (Lopez-Riquelme et al., 2009) at an ecological enterprise for cabbage crop. The sensor successfully measured various soil characteristics such as temperature, volumetric moisture content and salinity.

2.4 Measurement of soil properties with proximal soil sensors

Soil testing/analysis is an essential part of vegetable crop agronomy, which enable targeting of production inputs (e.g. fertilisers) and optimisation of management practices (e.g. liming for disease management and soil organic matter as an indicator of soil health). This is particularly important on rented land where much of UK vegetables are grown. Potentially, proximal or ground-based (invasive or non-invasive) soil sensors have the ability to collect high resolution data rapidly, and in certain cases even allowing real-time analysis and processing, by taking measurements as frequently as one per second (Viscarra Rossel and McBratney, 1998). Sensor-based soil analysis potentially provides several advantages over conventional laboratory methods such as lower cost, increased efficiency, more timely results, and collection of dense datasets while just traversing a field.

Adamchuk *et al.,* (2004) categorized different on-line soil sensors in six main categories based on their design concepts, including electrical and electromagnetic, optical and radiometrics, mechanical, acoustic, pneumatic and electrochemical soil sensors. The authors added that the output of majority of the soil sensors is affected by more than one agronomic soil characteristic. Kuang et al. (2012) suggested the following 6 categories that can be used for laboratory, *in situ* or off-line and on-line measurement conditions:

1. Reflectance based soil sensors (e.g. visible and near infrared (vis-NIR), mid infrared (MIR) spectroscopy).
2. Conductivity, resistivity, and permittivity based soil sensors (e.g. electromagnetic induction (EMI), electrical resistivity (ER), etc.
3. Passive radiometric based soil sensors (gamma ray)
4. Strength based soil sensors (draught sensors, and penetrometers), and
5. Electro-chemical based soil sensors (ion selective electrodes (ISE)

Authors concluded that that some techniques perform better than others for the measurement of a soil property. Due to technical issues, some techniques e.g. the MIR spectroscopy can only be used for laboratory analysis, whereas others e.g. EMI are used for field analysis only. Other methods e.g. EMI is better suited for detecting variability in soils. Another conclusion was that none of the sensors listed above can measure all soil properties essential for the management of the soil-plant-water system.

The accuracy obtained for a given soil property varies with the sensing method used and with the type of measurement, e.g. laboratory, *in situ* and on-line methods. A sensor producing a high correlation under one set of conditions, may show a very poor performance under different conditions for reasons not yet understood. A general trend confirms that the most accurate measurement can be achieved with laboratory methods, followed successively by *in situ* and on-line methods. The underperformance of the *in situ* and on-line as compared to the laboratory method is attributed to environmental factors, *e.g.* temperature, dust, roots and stones, etc. Another source of error associated with field calibration is that samples are collected at (slightly) different locations due to poor position (Mouazen et al., 2007) and possibly at different time than measurement with a sensor. Although the latter is ignorable, a slight difference in location between sensor data and a soil sample collected for calibration may yield significant errors, due to the large variability even at small as meters scale (Mouazen et al., 2007). Finally, and potentially most crucial, is the fact that only few sensing principles are able to measure a certain property directly based on the physical and/or chemical principle involved, for instance the measurement of OC and MC with vis-NIR spectroscopy and the use of ISE's and ISFET for measurement of macronutrients. Therefore, research is needed to improve current sensing technologies and develop new sensing techniques including the sensing infrastructure aiming at achieving a stable and consistent environment, which ensures a sensor to operate under varying environment in the field.

Some sensing techniques including among others acoustic, pneumatic and ground based passive radiometric based sensing using microwaves did not receive attention in this review, since only marginal advances in the development of these methods for soil analysis have been reported so far. It is worth to investigate these sensing principles further and even explore new techniques being used in other sectors for applications in agricultural soils.

Some properties cannot be measured directly with a sensing technique e.g. measurement of P with vis-NIR spectroscopy and this also holds for most properties measured with EMI and gamma ray spectroscopy. The successful measurement of these properties is attributed to co-variation with other soil properties e.g. with OC in the NIR spectroscopy (Stenberg *et al*., 2010). As the origin of these co-variations is not yet understood nor documented in details, authors recommended further research. Additionally, given this limited understanding, successful calibration of sensors may only be improved by continuous calibrations using the largest possible data, which increases the cost of analysis. Still, as compared to conventional sampling methods, dense datasets that can be obtained with current sensor technology might increase the overall spatial estimation accuracy even if the accuracy of individual measurements is lower than existing conventional methods (Sudduth et al., 1997). Authors' final conclusion was there is a need for multi-sensor and data fusion to extract the most valuable data for site specific land management. A later published literature by Halcro et al. (2013) suggests the need for data fusion not only on soil properties but also crop biomass, weather, topography and yield.

On-line soil sensors refer to those sensing technologies used to collect data while moving across a landscape. An on-line sensor to measure key soil properties based on vis-NIR spectroscopy is an example (Mouazen et al., 2007). In addition to the main benefit of on–line sensors (mapping the spatial variation in soil at field/subfield scale with high sampling resolution), the output of these sensors is valuable input for decision support. There are several examples to illustrate how data collected with on-line sensors can be used for variable rate applications (VRA) in precision agriculture. The literature identifies two types of VRAs (Morgan and Hess, 1997), namely map-based and sensor-based applications. The former relies on recommendation maps developed *prior* to an application event. The availability of satellite navigation system such as the Navstar GPS (Global Positioning System) on agricultural machinery enables the electronic controller to associate the time, location and output rate to produce an "as applied map" (Miller, 2003). This may be produced in-cab or back on farm computer. These maps are developed by dividing the field into management zones based on on-line sensor output only or by combining this output with crop information (Vrindts et al., 2005), farmer experience and other ancillary data. The sensor-based VRA is based only on data collected automatically by on-line sensors and models that transfer sensor output into application (e.g. Maleki et al., 2008). However, no literature is available about using the on-line vis-NIR spectroscopy for VR fertilisation recommendation in vegetable crop production.

Only three innovative on-line measurement systems of soil properties are available in the world, one of which is being available at Cranfield University. This sensor is identical to the system developed previously in the Catholic University of Leuven in Belgium (Mouazen, 2006). Primary tests proved the system to measure successfully soil MC (Mouazen et al., 2005), TC and TN, OC and ON, pH and P (Mouazen et al., 2007) for soils in Belgium and Northern France. However, these models were developed with a shorter wavelength spectrophotometer (AgroSpec 350-2200 nm from tec5 Technology for Spectroscopy, Germany), so that they are not compatible with the current technology advancement. Using a vis-NIR spectrophotometer with a larger wavelength range than the old version as this is available in Cranfield University had led to much improved accuracy for the measurement of TN, OC and MC in 5 European countries (Kuang and Mouazen, 2011a). In the UK the system was used to measure TN, OC and MC in arable fields at the Cranfield University experimental farm (Kuang and Mouazen, 2011b) and to measure TN in selected fields with vegetable crop production (Fang, 2011). Less accuracy for the measurement of TN was found in these fields as compared to measurement in arable fields, which might be due to different soil chemistry that requires the development of new calibration models valid for soils with vegetable crop production. Furthermore, this on-line sensor has not been utilised to provide input data for VR fertilisation in vegetable crop production sector so far.

Most of proximal sensing applications reported so far were for arable crops. Literature suggests very small number of applications of these technologies particularly in vegetable crop production. Perhaps the most common horticultural application is the use of EMI to map spatial variability in the field to guide variable rate irrigation (Monaghan *et al*, 2013).

2.4.1 Multi-sensor and data fusion

Due to the complex nature of agricultural soils, sensors generally react to (many) more than one property and this will strongly limit their use. As an example, readings from a frequently used sensor as the EM38 are influenced by clay content, soil salinity, MC, density and temperature. This, with varying degrees of sensitivity, might apply to some other sensors. Combining or integrating data from different soil measuring concepts, a process often referred to as “fusion” may produce complementary information on specific soil property, improve the accuracy of measurements and predictions, and permit exploring a wider range of soil properties. Fusion can be achieved following different approaches:

(a) Multiple sensors where a set of sensors is assembled on the same platform to measure multiple soil properties simultaneously (Taylor et al., 2006; Mouazen and Ramon, 2006). This may allow an integrated processing of the output signals of the sensors when physical and chemical principles are matching. Research on this concept is reported by Mouazen (2009). A field experiment cultivated with tomato in Italy, De Benedetto et al. (2013) implemented multi-sensor and data fusion approach to delineate management zones for site specific irrigation. Authors proved this approach to be effective in improving the vegetation response to water stress conditions, concluding that crop could be more sensitive water management than soil properties. Mouazen et al. (2013) reported a successful fusion of multi-sensor data of an EMI and on-line vis-NIR sensors for the delineation on management zones for site specific irrigation in vegetable crop production systems. The fusion of information on soil ECa, organic carbon, moisture content, clay content and plasticity index allowed the derivation of a water holding capacity index, which is a useful index for optimising the position of water sensors and for informing variable rate irrigation strategy. Multi-sensor technology consisting of on-line vis-NIR spectroscopy, bulk density sensor and EMI sensor were successfully implemented for the delineation of management zones for variable rate irrigation (Mouazen et al., 2014).

(b) Data fusion on soil where data are collected with different sensors on the same field. The output of the soil sensor is interpreted on an individual basis, and data fusion is achieved by means of advanced geostatistics (Mahmood et al., 2011) and data fusion techniques like Kalman filter. In this instance, data from proximal soil sensing might be integrated with those from *in situ*, laboratory and on-line data. However, data from different on-line sensors can also be integrated. For example, EMI scanning is recommended as the first sensing method to be implemented, by which within field variability associated mainly with texture and MC can be established. Other techniques can then be implemented to detect quantitative variation in key soil properties for soil-plant-water management.

(c) Data fusion on soil and crop (NDVI, vegetation cover, yield, etc.) are integrated with other ancillary data on field topography, weeds, pests and diseases, weather etc. (Halcro et al., 2013). This information will differ in (spatial) resolution and time, as data collection may span more than one cropping season. This approach requires detailed knowledge of the locations where data are collected (GPS systems) and fusion must be based on sophisticated georeferencing and geostatistical techniques, as these data differ in resolution and in time. Paoli et al. (2005) fused data on grape yield, soil depth and qualitative data associated with expert knowledge on quality of grapes at different zones across a field.

2.4.2 Proximal soil sensors in horticulture

By reviewing the available literature on the use of proximal soil sensors in horticulture one can easily come to the conclusion that there are not many applications exist with the majority directed towards viticulture. Here are some of the research found on the most known precision agriculture journals and books.

- Research reports based on traditional soil sample collection followed by laboratory analyses with reference method are enormous (e.g. Aggelopoulou et al., 2007).
- EMI has been used quite broadly in horticulture to assist mapping the within field variation in soil properties. It has been used to assist optimising the sampling position for soil samples collected for laboratory analysis with reference methods (e.g. Urretavizcaya et al., 2013). De Benedetto et al. (2013) used an EMI as a proximal soil sensor to collect data on apparent electrical conductivity (ECa). The ECa was fused with crop data collected with satellite imagery and proximal crop sensors to

delineate management zones for site specific irrigation in tomato production.

2.4.3 Variable rate applications in vegetable crops

Maguire et al. (2003) investigated the use of an automated system capable of varying onion seed rates according to pre-determined application plan. An AGCO field stare variable rate controller used on white planters was adapted for use with a Stanhay Singulaire 780 precision drill, which resulted in satisfactorily performance with a mean error in seed spacing between actual and required of 2.57% in the laboratory and 3.15% in the field. This led to a 10% increase in the saleable yield of onion.

The potential to improve nutrient use efficiency and therefore, yield and quality, is essential to help contribute vegetable sector to be more competitive and sustainable. Defra (2010) explains the basis of nitrogen recommendations. Figure 2-1 shows a typical nitrogen response curve, where applying nitrogen to soil improves their quality and, hence, crop yield. However, when applying too much nitrogen, there is a large amount that is not used by the crop and this surplus of fertiliser can increase the risk of nitrate leaching into the water. Besides water pollution this over-application of fertiliser in the soil causes a great financial cost to growers every season (Defra, 2010). These costs can be mitigated by an accurate application within the field.

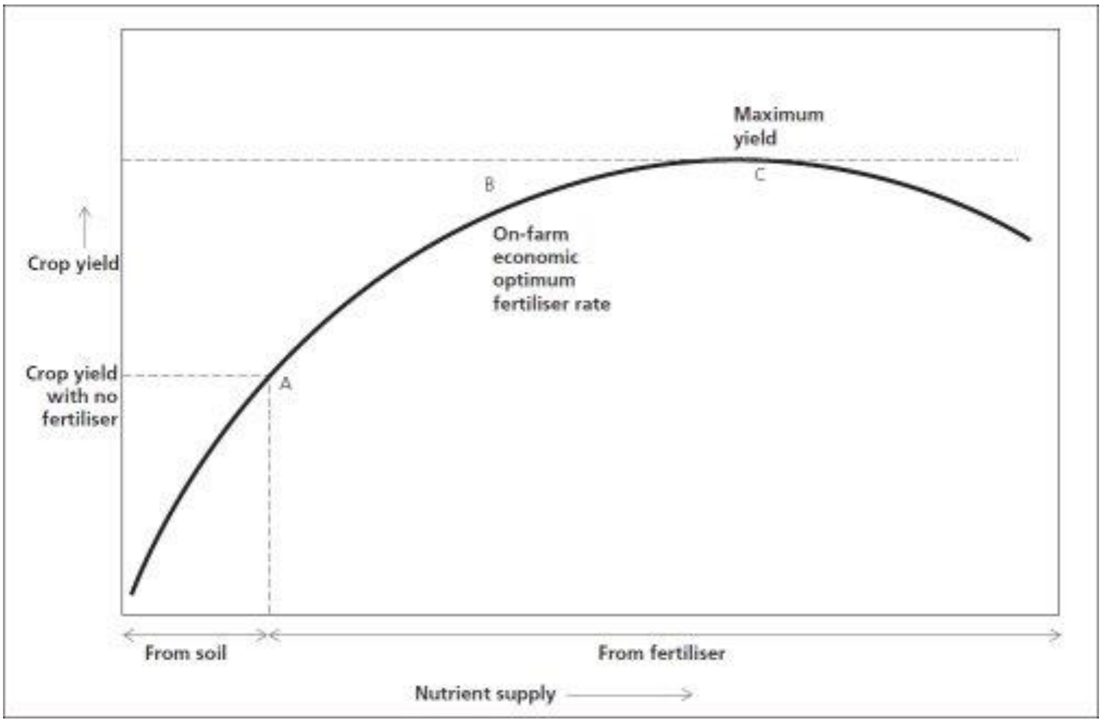


Figure 2-1 A typical nutrient response curve (Defra, 2010)

2.4.4 Delineation of management zones (MZ) as part of site-specific crop management

Management zone (MZ) can be defined as: “a portion of a field that expresses a homogeneous combination of yield-limiting factors for which a single rate – or more than one – of a specific crop input (seed rate, soil tillage, fertiliser rate, crop protection) is appropriate” (Doerge, 1998, quoted in Zhang *et al*., 2000; Fleming *et al*., 2000; Vrindts *et al*., 2005). Thus, each sub-region gets the appropriate level of inputs leading to reduce costs, improving profit potential and reducing environmental risks (i.e. leaching). The minimum size of a zone is limited by the ability of the farmer (including machinery) to manage regions within a field. Therefore, the basic aim of site-specific crop management of agricultural inputs (Stafford, 2000; Adamchuck *et al*., 2004) is to increase cost-effectiveness of crop production, improve yield quality and quantity, and protect the environment (in a short and long term basis). The importance of subdividing fields into smaller and homogeneous areas is the key for fertility management: applying fertilizers only where they are needed and when they are needed

(Bongiovanni and Lowenberg-Deboer, 2004). Goense (1997) implemented geo-statistics using soil parameters and a positioning system to calculate variability within the field for precision site specific fertilizer application. Vrindts *et al*. (2005) defined two different management zones by comparing soil and crop information measured with an on-line soil sensor. Two types of clustering were used to demonstrate yield variability in a winter wheat crop. One MZ was based on soil data (dry bulk density and soil moisture content), and a second MZ was based on soil and crop data. The results showed an unclear relationship between soil clusters and yield variability, while soil-crop clusters presented an inverse relationship between soil compaction and crop yield in some areas (dry bulk density above 1.6 mg/m^3 tend to reduce yield). Tagarakis *et al*. (2012) introduced different approaches to delineate yield and quality management zones in vineyards during two seasons, by measuring normalized difference vegetation index (NDVI) for canopy development, flowering, berry set, ripening and harvesting, soil electrical conductivity (EC_a), soil depth and topography. Delineated MZ generated with different input data (yield-based and quality-based) showed a high degree of agreement (79.2 and 89.6%). They reported a positive correlation between EC_a survey maps and yield production and a good correlation with NDVI and yield and quality at ripening time. Fleming *et al*. (2000a) defined effective management zone maps based on aerial photographs in Colorado, USA, comparing soil colour, topography and farmer experience to soil nutrient levels, texture, conductivity readings and crop yields. Based on this study, Fleming *et al*. (2000b) reported that MZ maps based on aerial photograph for variable rate technologies (VRT) in nitrogen application were equally effective but less cost-effective than grid soil sampling approach, and is an effective method in defining homogeneous sub-regions within a field. Van Alphen and Stoorvogel (2000) reported efficient reductions in fertilizer inputs (-23%) after applying split fertiliser using feed-back from crop monitoring as compared with regular procedures used by farmers (uniform rates advised by extension services), in three management units. A study carried out in Colorado (USA) on corn (*Zea mays* L.) fields (Koch *et al*., 2004) reported increased crop yield by applying different nitrogen rates utilizing a grid-based site-specific crop management (SSCM), highlighting that the VR nitrogen fields are more economical than the UR fields, where net returns were approximately $18-$29 per ha.

High spatial frequency of soil sampling can be a major problem in PA as this is a time consuming, costly and labour intensive. The soil analyses provide farmers information about soil fertility and potentially yield limiting factors. PA sensors can produce a high quantity of data from the crop and soil and sometimes overload the farm manager as processing it is time consuming, labour intensive and costly. The integration of high-technology tools, experts systems and development of proper decision support systems (DSS) is required to obtain a better response from inputs in agriculture (Stafford, 2000; McBratney *et al*., 2005). Therefore, an alternative soil sampling technique, enabling fast, cost effective, environmentally friendly and high resolution sampling is required to achieve goals of precision farming. The implementation of proximal sensing technologies plays a key role in the future of PA.

2.5 Conclusions

From the above literature review, the following conclusions can be drawn for further research needs in the vegetable sector:

1- Numerous examples of research on monitoring crop characteristics including, NDVI, water stress, etc. can be found in the literature, which include satellite imagery and ground based sensors. The variety of crop sensors used for this purpose was essential to control the use of fertilisers in site specifically scenarios. However, in all cases within measurement of field variation of soil properties with the same spatial resolution of that of crop characteristics measurement was not possible or not considered by scientists so far, and decision were made based on crop characteristics ‘only’, measured with different sensing techniques.

2- Although literature shows the existence of yield sensors, most studies focuses on predicting the yield potential using satellite imagery or ground based sensors. However, less evident on sensing yield quality could be found in the literature.

3- Proximal soil sensing has rarely been used to map the within field variation in soil properties to allow relating crop characteristics in the vegetable sector. It was not clear why this is the case, although many applications could be found for the arable production system. This emphasises the need for research on the implementation of proximal soil sensing methods, e.g. the vis-NIR spectroscopy, for optimising the input of vegetable production systems including fertilisers, irrigation, seed rate, etc.

4- Fusion of data on soil and crop with other information about weather and topography has been launched in the arable production systems. However, it was only possible to find a few in the vegetable system, which necessitates the need for studies on data fusion based on proximal sensors on crop and soil, with other auxiliary data.

CHAPTER 3. RESEARCH AIM AND OBJECTIVES

3.1 Research gaps

Research in PA has been focused mainly on cereal crops, where only little has been done on horticulture and vegetable sectors. Up until now, sensors applied in Precision Horticulture are mostly used for insect monitoring, weed infestation, caliper measurement and crop load scouting; especially in fruit trees. There is very limited literature available on variable rate fertilisation based on proximal soil sensors. No literature could be found so far for the use of the on-line vis-NIR sensors for informing variable rate application in vegetable crop systems.

This project will cover this gap by implementing the on-line vis-NIR sensor developed by Mouazen (2006) for on-line measurement of selected soil properties in farms producing vegetables crops (*Brassica Oleracea* spp.); to identify locations to apply optimal fertiliser rates for a better crop management that results in increased yield at reduced input cost.

3.2 Hypothesis

Fertiliser applications can be improved by acquiring high-resolution data to inform variable rate nitrogen fertilisation that results in increase yield and produce quality at reduced input cost. Additionally, for a better prediction performance, it is not always true to assume that field scale calibration models of vis-NIR spectroscopy will lead to the best prediction accuracy and that heterogeneous data set may result in improved prediction accuracy, as compared to calibrations based on field data.

3.3 Research aim

This research aims at using a previously developed tractor-mounted fibre-optic vis-NIR on-line sensor to measure some key soil properties, namely, organic carbon (OC), total nitrogen (TN), soil moisture content (MC), pH, extractable calcium (Ca_{ex}), extractable potassium (K_{ex}), extractable sodium (Na_{ex}) and available phosphorus (P_{avl}) to be used as an input data to refine within-field nitrogen fertiliser application in vegetable crop production system. This hypothesis will be tested under commercial *Brassica* spp. crop production systems in the United Kingdom (UK).

3.4 Research objectives

To achieve the aim described above, the following objectives will be pursued:

1- To develop a reliable vis-NIR calibration models to measure soil OC, TN, MC, and pH, using diverse spectral libraries and different geographical scale as a preliminary step towards the development of an automated variable rate nitrogen fertiliser distributor under *Brassica* spp. crop production.

2- From the on-line collected soil data, management zones (MZ) for VR nitrogen fertilisation will be delineated following three schemes: a uniform rate (UR) application and two variable rate (VR) applications. The first VR scheme (VR1) attempts to replicate the traditional method of mapping MZ, using thematic maps, whereas the second VR scheme (VR2) is based on an innovative high-resolution sensor system. This will lead into fertiliser recommendation maps that will determine the most efficient method for delineating MZ.

3- To evaluate the economic benefits of adopting site-specific nitrogen fertilisation based on on-line sensing of soil properties, fused with information about crop growth.

CHAPTER 4. MATERIAL AND METHODS

4.1 Optimising calibration and validation of the on-line soil sensor

The aim of this section was to compare the performance and accuracy of calibration models developed for MC, OC, pH and TN for individual farms (scenario 1) with that of general models at regional (scenario 2), national (scenario 3) and continental scales (scenario 4). The selection of these four properties was based on the fact that these are most linked with soil fertility. Four different calibration scenarios were developed and tested, using data collected from selected fields with vegetable production in 2013 and 2014 seasons, which was augmented with data collected earlier from UK and other EU countries. Modelling was based on different spectral libraries that reflect different geographical scales, variability of concentration and sample number. It also aimed at optimising the calibration and prediction among different scenarios tested to recommend this to predict the above mentioned four soil properties in five selected vegetable crop fields in the UK, measured with the on-line soil sensor during 2013 and 2014 season.

4.1.1 Experimental fields

Five fields with cauliflower and cabbage (*Brassica oleracea spp.*) crop production were selected to perform field measurement with the on-line vis-NIR sensor (Mouazen et al., 2005) during 2013 and 2014. They were located in Lincolnshire, UK (Figure 4-1), and were of loamy soils with flat topography. Detailed information about these fields is summarised in Table 4-1.

Table 4-1 Information of soil samples collected from 5 fields in Lincolnshire, UK in 2013 (OLD306 and MBHN01) and 2014 (BWX- fields).

Field ID	Field name	Location	Sample N	Area (ha)	Crop
OLD306	Oldershaw	Whaplode	100	17.5	Cauliflower
MBHN01	Needhams	Butterwick	64	11.1	Cabbage
BWX102	Johnnys-W	Carrington	60	24.5	Cauliflower
BWX103	Needhams	Carrington	34	12.3	Cauliflower
BWX104	Needhams	Carrington	27	9.8	Cauliflower

4.1.2 Soil samples

4.1.2.1 2013 growing season

A total of 164 soil samples were collected in this study, among which 111 were taken before the on-line measurement. The remaining 53 soil samples were hand-collected during the on-line measurement from the bottom trench of about 10-15 cm soil depth from two different fields (MBHN01 and OLD306) in Boston, Lincolnshire, UK. The sample position was carefully recorded using a DGPS (GeoExplorer ® 6000 series, Trimble, USA), in order to validate accuracy of the on-line soil sensor. The 111 soil samples were a composite of five separate soil cores, all collected from within 5 m radius of the recorded sample location, and mixed thoroughly, creating a bulked sample to reduce sampling error and return a more representative result (Oliver et al., 1997). About 300 g of soil was collected from each sample, stored in plastic bags and kept refrigerated (4 ˚C) until analysis (Mouazen et al., 2007). Half of each sample was used for optical measurement and the remaining samples were kept for soil chemical and physical analysis, in Cranfield University soil laboratories.

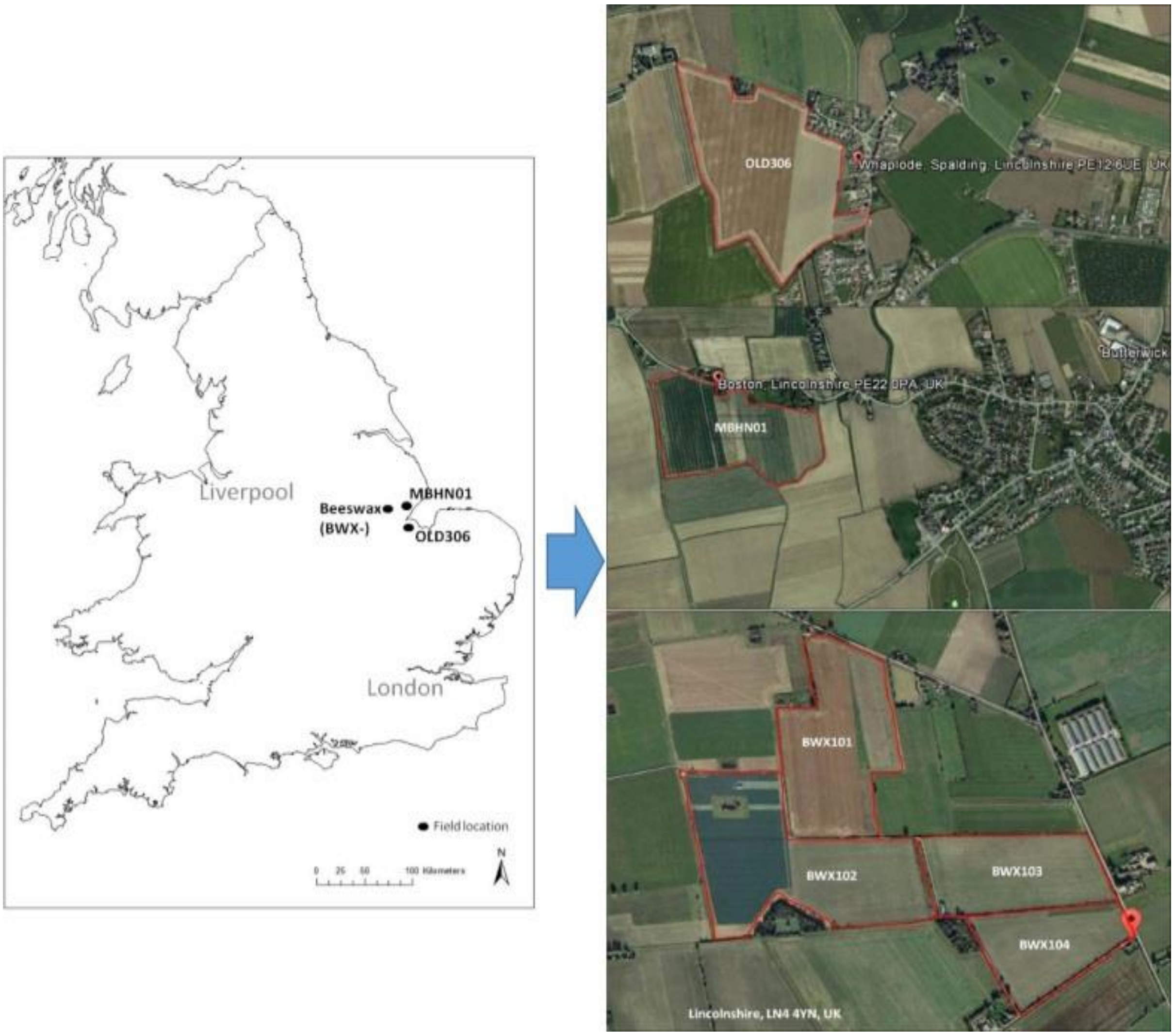


Figure 4-1 Location of the fields in Lincolnshire used in this study during 2013 and 2014.

4.1.2.2 2014 growing season

A total of 142 soil samples were analysed in this season, among which 59 samples were hand-collected before the on-line measurement, following the same procedure as in 2013. The remaining 83 samples were collected while the on-line measurement was carried out, to validate the measurements done with the on-line vis-NIR spectrophotometer sensor.

4.1.2.3 Other soil samples

For the remaining three strategies, namely, SC2 (regional), SC3 (national), and SC4 (continental), spectral libraries of different geographical scales were used.

Data collected from the fields in 2013 and 2014 were added to each strategy. While SC1 and SC2 samples were collected from vegetable crop fields, in SC3 and SC4 soil samples were collected from arable and vegetable crops. Samples from Europe fields were taken from different locations: Denmark (20), Czech Republic (25), Germany (42), and Holland (23). The soil data of these libraries were collected and processed in the same conditions.

4.1.3 Chemical analyses

The soil properties investigated in this study were OC, TN, MC, pH, Na_{ex}, K_{ex}, Ca_{ex}, Mg_{ex}, and P_{avl}. Laboratory analyses to measure these properties were carried out by NRM laboratories (www.nrm.uk, UK) and in the soil laboratories in Cranfield University using standard procedures described here. The samples were air dried, crushed and sieved with a 2 mm sieve. Soil pH was measured in water, using a soil:water ratio of 1:5. After shaking the sample for 1 hour and equilibration for another hour, pH was measured in the settling suspension and the result was reported as a dry basis. The P_{avl}, expressed in mg per 100 g of dry soil, was determined by using sodium hydrogen carbonate solution to obtain an extract. After the extract has been prepared, P_{avl} was measured by a colorimetric method (Olsen et al., 1954). The Na_{ex}, K_{ex}, Ca_{ex} and Mg_{ex} were measured in NRM laboratories following *DEFRA Reference Book 427* (Faithfull, 2002) standard procedures, determined by using barium chloride buffered at pH=8.1, identical to BS 7755 Section 3.12 (1996), and expressed in Cmol per kg of dry soil.

The parameters analysed at Cranfield soil laboratory were OC, TN, and MC. Soil OC and TN were measured by an elemental analyser vario EL III (Elementar, Germany) using catalytic combustion of the sample, based on British Standard (BS 7755 Section 3.8:1995). Soil MC was determined by gravimetric method, measured on fresh soil samples immediately after collecting samples by drying the soil samples on an oven at 105 ˚C for 24h. This method is based on BS 7755 Section 3.1:1994, which is identical to ISO 11465:1993.

Different calibration models for all studied properties were established and used to develop different maps. However, the statistical comparison between the reference and on-line measurements was performed using the calibration models of OC, TN, MC and pH only.

4.1.4 On-line vis-NIR measurements

The on-line measurement system designed and developed by Mouazen (2006) was used to measure two fields in Lincolnshire in June 2013 and three fields in May 2014, after the harvest of the previous crop. It consists of a subsoiler that penetrates the soil to a certain depth (0.15 m in the current work). An optical probe linked to the subsoiler heal was used to acquire soil spectra from the bottom of the trench, that has been opened and smoothed by the subsoiler chisel (Mouazen et al., 2005), as shown in Figure 4-2. The optical probe, housed in a steel lens holder collected soil spectra in diffuse reflectance mode. The subsoiler with the optical unit was attached to a frame, which was mounted onto the three point linkage of the tractor (Mouazen et al., 2005).

An AgroSpec mobile, fibre type, vis-NIR spectrophotometer (tec5 Technology for Spectroscopy, Germany) with a measurement range of 305-2200 nm was used to measure soil spectra in diffuse reflectance mode (Figure 4-2). The spectrometer was an IP 64, protected for harsh working environments. A differential global positioning system (DGPS) (EZ-Guide 250, Trimble, USA) was used to record the position of on-line measured spectra with sub-meter accuracy. A Panasonic semi-rugged laptop was used for data logging and communication. The spectrometer system, laptop and DGPS were powered by the tractor battery (Quraishi and Mouazen, 2013). In each field, namely OLD306, MBHN01, BWX102, BWX103, and BWX104, blocks of 20 m width and circa 400 m long, covering about 10 ha of land were measured in each field. The travel speed of the tractor was approximately 2 km/h and the measurement depth was set at 0.15 m. The main source of electrical power was the tractor's battery.

During the on-line measurement, 2-3 soil samples were taken from randomly selected positions in every row (Figure 4-3). The procedure of soil sampling was as follows: a wooden stick was used to mark each soil sample position, which corresponded to the position of underground soil reflectance spectra collected by the on-line sensor. After the on-line sensor travelled through the area, the soil surface was dug up and smoothed over by the on-line sensor and packed the soil samples in sealable plastic bags. A total of 136 fresh soil samples were collected within the five fields (circa 200g each) and the position was recorded.

Each sample was divided into two parts for validation analyses: one half was used for optical scanning, and the other half for laboratory reference measurements of soil OC, TN, MC, pH, Na_{ex}, Mg_{ex}, Ca_{ex}, K_{ex}, and P_{avl}.

The spectrometer was calibrated with a standard white reference disc; and measurements were taken before starting the experiment and were repeated every 30 minutes afterwards.

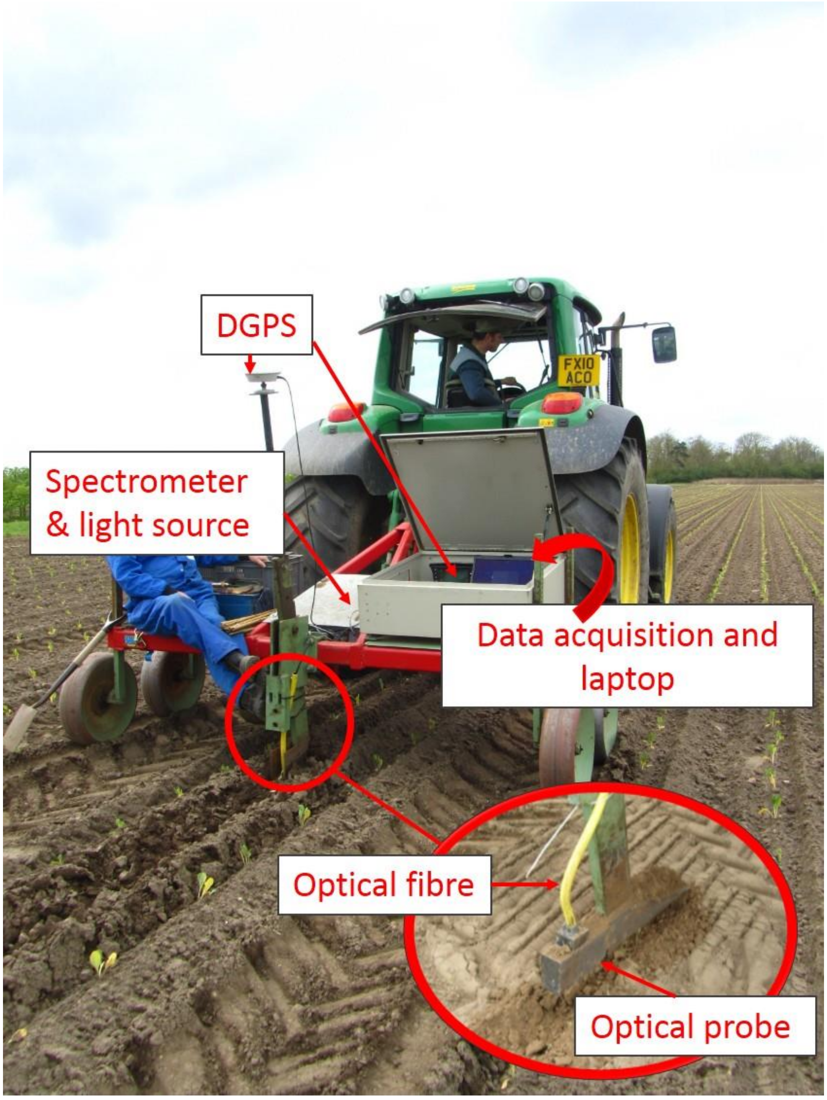


Figure 4-2 The on-line visible and near infrared (vis–NIR) spectroscopy-based sensor (Mouazen, 2006), attached to the tractor for on-line measurement, shown here operating between the rows of a brassica crop.

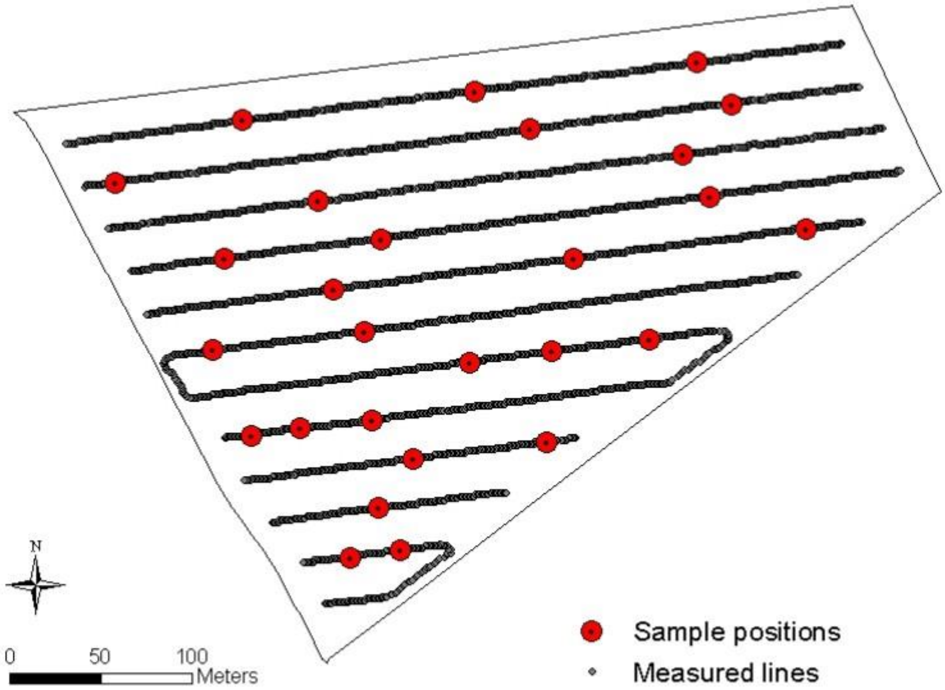


Figure 4-3 On-line measured lines and soil sampling positions during on-line measurement, shown for BWX104 field as an example

4.1.5 Optical measurements in the laboratory

Optical measurement was carried out in the laboratory on all 306 soil samples collected during the on-line measurement (136 prediction samples) in addition to 170 soil samples collected previously for calibration. Each soil sample was placed into a glass container and mixed well, where big stones and plant residues were excluded. Then, each soil sample was placed into three petri dishes (2 cm depth x 2 cm diameter). The soil in the petri dish was shaken and pressed gently before levelling with a spatula to ensure a smooth surface and, therefore, a maximum light reflection and a large signal-to-noise ratio (Mouazen et al., 2005). The soil samples were scanned with the same AgroSpec vis-NIR spectrophotometer (tec5 Technology for Spectroscopy, Germany) used during on-line field measurement. The spectrometer was calibrated with a standard 100% white reference disc. The white reference was measured several times before starting the experiment and every 30 minutes during work measurements. A total of 30 scans were collected from each soil sample and these were averaged into one spectrum, representing a particular sample.

4.1.6 Data pre-treatment and development of calibration models

For the spectral data, the same pre-treatment was carried out for all the soil properties studied in this research, using The Unscrambler 9.8 software (Camo Inc., Oslo, Norway). In a first step of pre-treatment, spectra were reduced to 305-2200 nm to erase the noise at both edges of each spectrum. After noise was removed, spectra were reduced by averaging three successive wavelengths in the visible range (305-1000 nm) and fifteen (only six in case of pH) successive wavelengths for the NIR region (1001-2200 nm). Averaging over wavelengths was done to decrease the number of wavelengths and to smooth the spectrum (Nicola et al., 2007). Maximum normalization was followed, which is typically used to get all data to approximately the same scale, and data was ´polarized´. The peaks of all spectra with positive values are scaled to +1, while spectra with negative values were scaled with -1 (Mouazen et al., 2005). Spectra were then subjected to Savitzky-Golay first derivation (Martens and Naes, 1989). This method enables the computation of the first- or higher-order derivatives, including a smoothing factor, which determines how many adjacent variables to be used to estimate the polynomial approximation used for derivatives (Kuang and Mouazen, 2013). A second-order polynomial approximation was selected. A 2:2 Savitzky-Golay smoothing was carried out to remove noise from spectra.

The pre-treated spectra and laboratory results of chemical analyses were used to develop the calibration models for the different soil properties mentioned above. Soil spectra were divided into cross-validation (75%) and prediction (25%) sets (Table 4-2).

Table 4-2 Sample statistics of 2013 calibration set used for partial least squares (PLS) regression cross-validation (75% of samples) and prediction set (25% of samples).

	Samples	Calibration set				Prediction set			
	n	Min	Max	Mean	SD	Min	Max	Mean	SD
SC1									
MC (%)	136	11.65	19.13	15.72	1.43	7.90	20.63	14.19	2.83
OC (%)	136	0.96	2.29	1.29	0.21	0.95	2.20	1.26	0.22
pH	136	5.30	8.50	7.45	0.73	6.00	8.10	7.31	0.41
TN (%)	136	0.10	0.19	0.13	0.02	0.12	0.20	0.15	0.02
SC2									
MC (%)	286	9.60	29.08	19.32	3.89	12.60	26.30	19.54	3.87
OC (%)	286	0.96	2.29	1.29	0.19	1.01	1.61	1.27	0.15
pH	286	5.30	8.80	7.91	0.71	5.80	8.70	7.98	0.69
TN (%)	286	0.09	0.19	0.14	0.02	0.10	0.18	0.13	0.02
SC3									
MC (%)	471	5.92	29.08	17.87	4.50	6.53	29.08	17.59	4.74
OC (%)	472	0.96	3.43	1.58	0.46	1.00	3.70	1.58	0.49
pH	387	4.87	8.70	7.59	0.91	5.24	8.80	7.56	1.03
TN (%)	424	0.09	0.19	0.13	0.02	0.10	0.34	0.16	0.05
SC4									
MC (%)	502	6.53	27.74	17.89	4.50	5.92	29.08	17.80	4.39
OC (%)	556	0.96	3.70	1.60	0.47	1.01	2.93	1.59	0.43
pH	496	5.08	8.70	7.58	0.86	4.87	8.80	7.60	0.95
TN (%)	456	0.09	0.39	0.16	0.06	0.10	0.32	0.16	0.05

[a] In SC1 only 136 samples were collected and used as calibration set and 53 fresh soil samples were collected while on-line measurement for the prediction set.

The calibration spectra were subjected to partial least squares regression (PLSR) with leave-one-out cross validation, using The Unscrambler 9.8 software (Camo Inc., Oslo, Norway). The residual variance was plotted against the number of latent variables obtained from PLSR. Then, the latent variable of the first minimum value of residual variance was selected (Kuang and Mouazen, 2011a). Outliers were detected by using residual sample variance plot after PLSR. Samples located individually far from zero line of residual variance were considered to be outliers and were excluded from the analysis. Calibration models were developed for each soil property using the following four different case scenarios (Table 4-2 and Table 4-3):

1- Scenario 1 (SC1; n=136) – Local calibration where samples from three fields with vegetable production in Boston, UK were used;

2- Scenario 2 (SC2; n=286) – Regional calibration where samples from fields with vegetable production in Lincolnshire, UK were used;

3- Scenario 3 (SC3; n=472) – National calibration where samples from fields with vegetable and arable crop production in the UK were used; and

4- Scenario 4 (SC4; n=556) – Continental calibration where samples from fields with vegetable and arable crop production in different EU countries were used. This included samples from Germany, Denmark, the Netherlands, Czech Republic and the UK.

The pre-processed spectra and the results of laboratory chemical analysis, along with the spectral libraries were used to develop the general calibration models for soil OC, TN, MC, and pH. In total, sixteen calibration models were generated: four for each property. The calibration models in cross-validation were validated for on-line measurement using the 53 samples and 83 samples in 2013 and 2014, respectively, collected from the fields during the on-line measurement.

For SC2, SC3 and SC4, the entire data was split randomly into two replicates of 75% and 25% for the cross validation set and prediction set, respectively. The number of samples in SC1 in both studied years is very small, so the entire number of samples was used for cross-validation, and the samples collected during the on-line measurement (n=53 in 2013; n=83 in 2014) were used to validate the models.

Table 4-3 Four different modelling scenarios and soil samples used to establish and validate general calibration models for measurement of soil moisture content (MC), organic carbon (OC), pH and total nitrogen (TN) in 2013 and 2014.

	Scenario	ID	*n*	Scale		Number of fields
2013	Scenario1	SC1	136	Local	Samples from Boston, UK[a]	3
	Scenario2	SC2	286	Regional	Samples from Lincolnshire, UK[a]	7
	Scenario3	SC3	472	National	Samples from UK[b]	14
	Scenario4	SC4	556	Continental	Samples from Europe[b]	22
2014	Scenario1	SC1	216	Local	Samples from Boston, UK[a]	8
	Scenario2	SC2	366	Regional	Samples from Lincolnshire, UK[a]	12
	Scenario3	SC3	555	National	Samples from UK[b]	19
	Scenario4	SC4	611	Continental	Samples from Europe[b]	27

[a] Samples from vegetable crop fields
[b] Samples from vegetable and arable crop fields across Europe (Denmark, Czech Republic, Germany, Holland and UK)

4.1.7 Performance assessment of calibration models

The accuracy of calibration and prediction of the models developed was determined by the smallest root mean square error of prediction (RMSEP), the largest coefficient of determination (R^2), and residual prediction deviation (RPD), which is the ratio of the standard deviation of the laboratory measured data to the RMSEP of the prediction set. Viscarra Rossel et al. (2006) classification for RPD was adopted in this study: RPD < 1 indicates very poor model/predictions and their use is not recommended; RPD between 1.0 and 1.4 indicates poor model/predictions where only high and low values are distinguishable; RPD between 1.4 and 1.8 indicates fair or moderately good model/predictions which may be used for assessment and correlation; RPD values between 1.8 and 2.0 indicates good model/predictions; RPD between 2.0 and 2.5 indicates very good quantitative model predictions, and RPD > 2.5 indicates excellent model/predictions. This classification index was used in this study to compare the performance between different models.

4.2 Satellite imagery for derivation of NDVI

In spring 2014, before harvesting, crop cover was measured in order to calculate the Normalised Difference Vegetation Index (NDVI) for three fields studied in 2014 (BWX102, BWX103, and BWX104); using LANDSAT 8

OLI/TIRS (Operational Land Imager / Thermal Infrared Sensor) satellite (U.S. Geological Survey, 2014). Satellite data was downloaded and processed. Firstly, after downloading and uncompressing the data, a conversion from OLI to Top of Atmosphere (TOA) radiance (without correction for solar angle) was implemented for the NIR and red spectral bands using the radiance rescaling factors provided in the metadata file. This conversion to radiance is processed by the application of the following equation:

$$L_{\lambda} = M_L Q_{cal} + A_L \tag{4-1}$$

Where:

L_{λ} = TOA spectral radiance (Watts/ (m^2*srad*μm))

M_L= Band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where x is the band number)

A_L= Band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x, where x is the band number)

Q_{cal}= Quantified and calibrated standard product pixel values (DN).

After the conversion, NDVI was calculated with the following equation:

$$NDVI = \frac{L_{NIR} - L_{Red}}{L_{NIR} + L_{Red}} \tag{4-2}$$

The result of the NDVI, calculated for every pixel in every daily orbital pass, is a value between -1.0 and 1.0, where 1.0 represents maximum photosynthetic activity, and thus maximum density and vigour of green vegetation.

The NDVI maps generated for each field were considered as other variable, along to the thematic soil maps, to produce the management zone maps.

4.3 Mapping

Maps were generated for every soil property and subsequently, management zone maps were also generated.

For the development of soil maps, two types were generated, namely, full point maps and comparison maps. The full point maps were developed using all on-line data points (c.a. 1500 – 2000 points per hectare). Firstly, all the negative values and non-soil spectra were removed. In order to develop semivariogram models for OC, TN, MC, pH, Na_{ex}, K_{ex}, Ca_{ex}, and Mg_{ex}, VESPER© 1.6 software, developed by Australian Centre of Precision Agriculture, was used (Quraishi and Mouazen, 2013). This program adapts itself spatially in the presence of distinct differences in local structure over the whole field. The local variogram is modelled in the program by fitting a variogram model automatically through the non-linear least squares method. After that, the semivariogram model parameters, including nugget, sill and range for each mentioned property were recorded. Based on semivariogram parameters and kriging interpolation method, ArcGIS 10 (ESRI Inc., USA) software was used to produce the full point maps.

The comparison maps were developed to compare on-line predicted versus laboratory reference measurement of a soil property, based on randomly selected point in the field (validation samples). These maps were developed for each property analysed in this study using ArcGIS 10 (ESRI Inc., USA) software and applying inverse distance weighing (IDW) method, because the number of points used here were not enough to apply the kriging method accurately. The comparison maps were created for fields studied in 2013 only, i.e. MBHN01 and OLD306.

To generate management zone maps, soil information and NDVI data were clustered using Vesper 1.6 (ACPA, Australia) and Statistica software (StatSoft Inc., USA). These cluster groups were based on the similar interaction between soil properties and NDVI data within a field. Then these data were imported to ArcGIS 10 (ESRI Inc., USA) and the cluster map was developed. Smoothing technique was applied to merge small potential management zones to neighbours, where appropriate.

4.4 Site specific N fertilisation

Site-specific nutrient management is an important area within precision agriculture. If different zones are identified within the field, growers can optimise inputs according to what they need to produce crop. If fertiliser application is limited to where, when and how much is needed, environmental pollution will decrease and the grower inputs will be less, which means better profit.

In this study, management zones were delineated by using different inputs and were compared between them to estimate which one performs better in order to apply nitrogen fertiliser.

4.4.1 Delineation of fertility zone maps

Soil spatial variability within a field requires different treatments. The benefits of applying the right amount of fertiliser where it is needed can be done by delineating management zones (MZ). Three different treatments for N fertiliser application were considered in this study:

i) The uniform rate (UR) application, which is based on the farmer's usual method in accordance with the *Fertiliser Manual (RB209)* (Department of Environmental, Food and Rural Affairs (Defra), 2010) recommendations for *Brassica* spp. crops, soil type and off-take strategy. This was considered as the control treatment.

ii) The first variable rate (VR1) application, which replicates the traditional VR method, known to be based on a thematic map and commonly used by commercial companies in arable crops. This technique was introduced in vegetable crops in this study to compare this approach against the one developed with vis-NIR technologies (explained below). Usually, 1 to 2 samples per hectare are collected from each field. STATISTICA software (StatSoft Inc., USA) was used to combine the different soil layers, by applying k-means clustering to group areas of similar fertility. The output was management zone (MZ) maps. The relative fertility for each zone in the MZ maps was decided with the analysis of the cluster means of the input properties.

Cluster with the strongest correlation with NDVI was considered the most fertile and received the least amount of N fertiliser and vice versa. This MZ map provided the basis for the fertiliser application map.

iii) The second VR scheme, designated as VR2, was based on the on-line vis-NIR sensor measurements and NDVI data obtained from the satellite imagery. As in VR1, k-mean clustering was applied to create MZ maps, and to merge small/irregular areas with neighbours or areas with similar fertility. The fertility index of each cluster was determined as in VR1.

4.4.1.1 2013 experiment

Direct comparisons between UR, VR1 and VR2 for N fertilisation was carried out by employing three adjacent plots with three replicates (Figure 4-4).

Each plot in the two experimental fields was 24 m wide and approximately 400-500 m long. The order of the three treatments was randomly chosen. Three plots of three treatments were spread over the width of both fields and the edge effects were reduced by making a 4 m buffer, as well as avoiding the tractor turning areas at the end of each tramline. A Kuhn Aero 2224 fertiliser spreader was used in this experiment to spread ammonium nitrate (NH_4NO_3) fertiliser with a 34.5% of total Nitrogen.

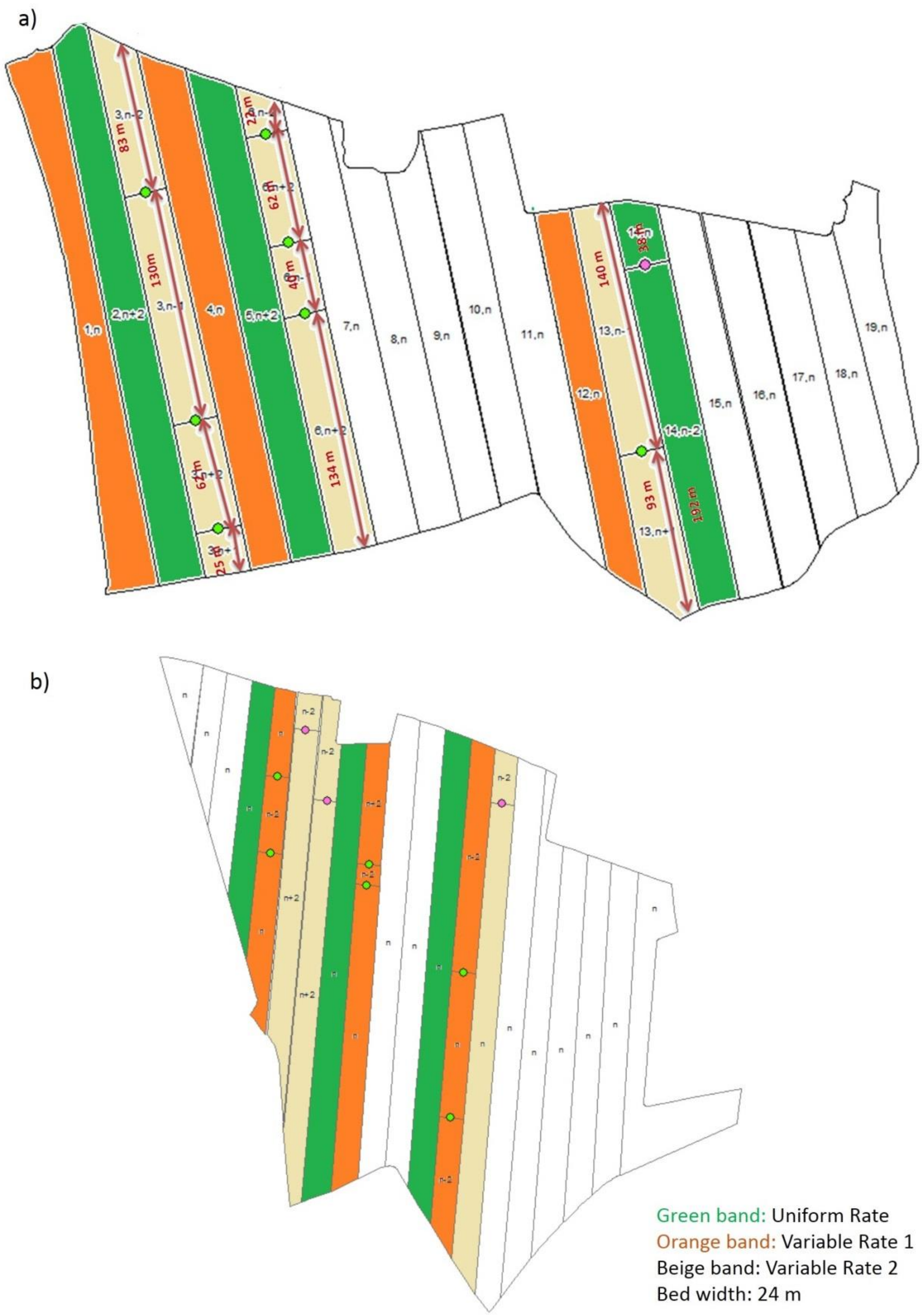


Figure 4-4 Study area and 24 m wide treatment plots in fields MBHN01 (a) and OLD306 (b).

4.4.1.2 2014 experiment

Management zones were delineated in three experimental fields following VR1 and VR2 procedures and then compared to UR treatment. These MZ maps were generated with the composition layers of soil MC, pH, OC, TN, and NDVI maps. Since variable rate application was not possible to implement due to the time pressure from the industry, only virtual calculation of fertilisation plot was possible. The fertilisation recommendation plot experiment map, delineated in ArcMap is shown in Figure 4-5 for BWX104 field, shown as an example. Different treatment applications of UR and VR1 and VR2 were assigned randomly.

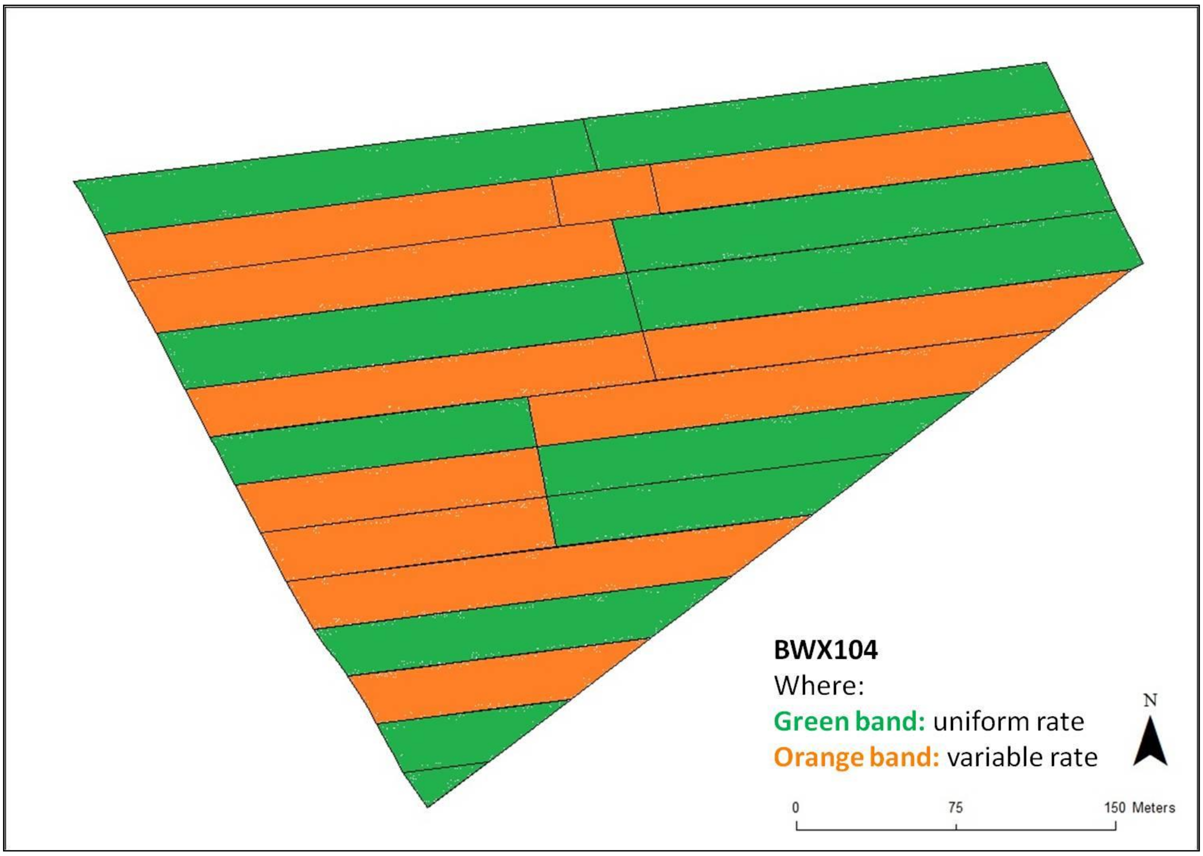


Figure 4-5 Plan of the study area and treatment plots in BWX104 used in simulation.

4.4.2 Derivation of N fertilisation recommendations

4.4.2.1 2013 experiment

The estimation of the amount of nitrogen fertiliser applied on the fields following both VR applications, formed the basis of five application rates chosen with the middle fertility zone as the one recommended by Defra (2010) for the crop and soil type (i.e. 290 kg/ha). Higher and lower rates of 10% were chosen based on the fertility of the MZ (Table 4-4), determined by the normal mean plots. It was assumed that areas with higher fertility will need fewer amounts of N application to reach the optimum crop growth and vice versa.

Table 4-4 Assignment of fertiliser application rates, 2013.

Method	Class	MZ relative fertility	Variable Rate	Total N applied (kg/ha)
UR	n/a	n/a	N	290
VR1	5	Lowest	N + 20 %	348
	3	Medium	N	290
	1	Highest	N - 20%	232
VR2	5	Lowest	N + 20 %	348
	4	Low-medium	N + 10 %	319
	3	Medium	N	290
	2	High-medium	N - 10 %	261
	1	Highest	N- 20 %	232

4.4.2.2 2014 experiment

The estimation of fertiliser recommendations for the fields in 2014 formed the basis of 5 application rates (Table 4-5). In this case, the rates chosen were comprised between 50 per cent above and below RB209 fertiliser recommendations split up in 25% ranges. This decision of large N rates (50%) was made in order to allow observing differences in crop responses between different rate applications. It is important to note that in 2014 only virtual calculation of N fertiliser need was made, and no VR experiment was followed as in 2013 experiment. This is because of the time pressure from the industry side, which led to apply N fertiliser based on their traditional methods.

Table 4-5 Assignment of fertiliser application rates, 2014.

Method	Class	MZ relative fertility	Variable Rate	Total N applied (kg/ha)
UR	n/a	n/a	N	290
VR1, VR2	5	Lowest	N + 50%	435
	4	Low-medium	N + 25%	362.5
	3	Medium	N	290
	2	High-medium	N - 25%	217.5
	1	Highest	N - 50%	145

4.4.3 Measurement of crop responses for 2013 experiment

Achieving the right timing of nutrient application is as important as applying the correct amount. Rapid development of leaves and roots during the early stages of plant growth is crucial to reach optimum yield at harvest, hence, an adequate supply of all nutrients must be available during this time (Defra, 2010).

The objective of the crop quality survey was to measure some crop physiological parameters over time and see how they correlated with the different fertiliser treatments that have been applied within the fields. A total of three measurements were carried out before harvest, during August, September and October 2013.

Sampling design was established as follows:

Due to the fact, that no N fertilisation was possible to implement in the fields of 2014, measurement of crop response was only carried out in the two experimental fields in 2013. An initial target of three replicates per treatment was implemented in OLD306 and four replicates per treatment in MBHN01. Due to relatively low planting density of cauliflower, a 5x5 plant quadrat was used at each location, enclosing 25 plants, out of which nine randomly plants were selected (Figure 4-6 and Figure 4-6). Each position was located equidistant between the tramlines to minimise edge effects. Thus, it was decided to carry out measurement of crop responses as far as three rows from the tramline. In addition, placing the plot in the middle of the strip was avoided, since this area is usually an overlapped zone. A wood stick was placed in the centre of the quadrat plot as a reference for the following measurements and was recorded with a DGPS. A total of 27 experimental plots with 243 cauliflower measurements were placed in OLD306, whereas a total of 36 plots with 324 cauliflower measurements were placed in MBHN01. The physiological parameters to measure were: height (cm), leaf colour, number of leaves, crown diameter (cm), curd initiation and curd diameter (cm). These measurements were taken in three occasions in OLD 306 and in two for MBHN01 before harvesting, between August and October 2013.

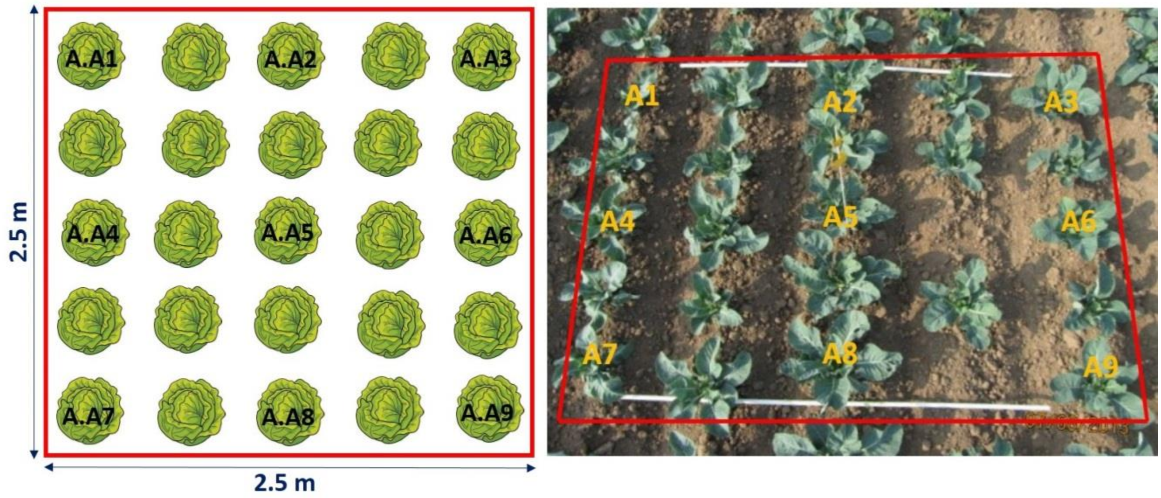


Figure 4-6 Plan of the experimental plots used for physiological measurements of crop response in 2013 in MBHN01 (right) and OLD306.

Following an *industry specification sheet* from one retailer in UK, an approximate calculation of marketable yield data was made. The main specification was the curd size, as it is the final product that goes to the supermarket shelves. However, number of leaves, height, and crown size were analysed through time, since they provide an effective means of examining any differences in growth.

4.4.4 Cost-benefit analysis

One of the challenges of precision agriculture is to optimise inputs and increase outputs, i.e., getting more with less. If famer's profits can be improved by reducing the amount of inputs and maintaining good harvest yields while reducing negative impacts on the environment, such as application of chemicals, PA will achieve the target.

Economic optimisation and partial budgeting are the most common methods used in the economic evaluation of variable rate technologies (Wang et al, 2003). The former is obtained when net return is maximised and marginal revenues equals marginal cost of production. Partial budgeting calculates changes in profit due to changes in inputs (Wang et al, 2003).

The objective of the cost-benefit analysis was to evaluate the economic benefits of adopting site-specific nitrogen fertiliser based on the new concept of fusion of data on soil (e.g. measured with the on-line sensor) with crop data (measured as NDVI with satellite imagery) (VR2) against uniform rate (UR) and traditional variable rate (VR1). To calculate the amount spent (in £/ha) for N-fertiliser in each field and each treatment, an estimation of the quantity of fertiliser to be applied on each management zone of each field, reported in kg/ha, was done. The product price range in £/t was obtained from AHDB-DairyCo (2015) available at its webpage. Thus, the economic costs between treatment applications were calculated and a comparison of site-specific management was analysed.

The cost-benefit analysis in the two experimental fields in 2013 was done by taking into account the input cost and output yield. However, since it was not possible to implement the fertilisation comparison experiment in 2014, only virtual calculation of input fertiliser cost was possible to carry out. This allowed only input cost to be compared between UR, VR1 and VR2 treatments.

CHAPTER 5. RESULTS AND DISCUSSION

For robust calibration models of the vis-NIR spectral data, the selection of the calibration set should be made carefully so as to be representative for the samples used for validation. This is important as when these models are used in future predictions of new spectra, they should provide acceptable performance with accurate predictions. The following section will focus on the performance of the four modelling scenarios for the prediction of the four key soil fertility parameters, e.g. MC, OC, TN and pH.

The remaining part of this chapter will discuss the results of the experimental plots in 2013 and 2014, comparing the innovative VR approach of N fertiliser of this thesis (VR2) with traditional VR1 and UR. The comparison will include crop physiological responses and economic output.

5.1 Model performance in cross-validation and prediction

Examining the results in Table 5-1 and **Error! Reference source not found.**, reveal the accuracy of prediction of a property differed among different strategies. Among all four studied properties, the best results in cross-validation were obtained for MC, whereas the least successful calibration was possible for pH. The indirect spectral response of pH in the NIR range in comparison with the direct spectral response of MC, may explain this result (Stenberg et al., 2010). The best MC performing model was the regional SC2 (R^2 = 0.89; RPD = 3.09), followed by continental SC4 (R^2 = 0.88; RPD = 2.91). This high accuracy can be attributed to the clear absorption bands of MC at the first (1950 nm) and second overtones (1450 nm), which also diminished the importance of sample number (Kuang and Mouazen, 2012) and degree of sample variability (Kuang and Mouazen, 2011c) on model performance. The best model performance in the prediction set was for SC2 and SC4 (R^2 = 0.88; RPD = 2.72 and 2.79) for both fields.

Cross-validation for OC and TN better performed in SC3 (national) and SC4 (continental) scenarios than with SC1 (local) and SC2 (regional), with R^2 > 0.70 and RPD > than 2.11, indicating a very good quantitative model performance

(Viscarra Rossel et al., 2006). The good model performance of both OC and TN obtained in this work can be attributed to the direct spectral responses in the NIR range (Stenberg et al., 2010). However, RMSEP of these two properties were larger in SC3 and SC4 as compared to SC1 and SC2. These results are in agreement with those reported by Kuang and Mouazen (2011c), where they found improvement in R^2 and RPD for a data set with a larger variability, as compared to a data set with a smaller variability. However, they confirmed that with increasing sample variability RMSEP values also increase. The accuracies of prediction with the SC3 and SC4 (R^2 = 0.58-0.87 and RPD = 1.53-2.79) in the prediction set were generally better than with the SC1 and SC2 (R^2 = 0.18- 0.87 and RPD = 0.56-2.72). The higher values of SC1 and SC2 can be found only for MC.

Table 5-1 Results of partial least squares regression (PLSR) in cross-validation models and prediction set for 2013.

	Cross-validation			Prediction set		
	R^{2a}	RMSEP[b]	RPD[c]	R^2	RMSEP	RPD
SC1						
MC (%)	0.72	0.68	2.09	0.86	1.30	2.17
pH	0.72	0.34	2.12	0.18	0.74	0.56
OC (%)	0.58	0.12	1.80	0.24	0.20	1.12
TN (%)	0.55	0.01	1.55	0.33	0.02	0.97
SC2						
MC (%)	0.89	1.26	3.09	0.87	1.42	2.72
pH	0.72	0.36	1.96	0.64	0.41	1.68
OC (%)	0.54	0.11	1.67	0.29	0.14	1.08
TN (%)	0.65	0.01	1.75	0.42	0.01	1.28
SC3						
MC (%)	0.87	1.62	2.76	0.79	2.18	2.17
pH	0.81	0.39	2.34	0.82	0.43	2.37
OC (%)	0.76	0.21	2.19	0.58	0.32	1.53
TN (%)	0.81	0.02	2.38	0.75	0.03	2.00
SC4						
MC (%)	0.88	1.54	2.91	0.87	1.57	2.79
pH	0.78	0.38	2.26	0.74	0.48	1.97
OC (%)	0.70	0.22	2.11	0.62	0.27	1.61
TN (%)	0.80	0.02	2.41	0.76	0.03	2.02

[a] Coefficient of determination

[b] Root mean square error of prediction

[c] Residual prediction deviation (standard deviation/RMSEP)

SC1 (local samples); SC2 (regional samples); SC3 (national samples); SC4 (continental samples)

Table 5-2 Results of partial least squares regression (PLSR) in cross-validation models and prediction set for 2014 - 75% of the total samples for calibration and 25% for prediction set.

	Cross-validation			Prediction set		
	R^{2a}	RMSEP[b]	RPD[c]	R^2	RMSEP	RPD
SC1						
MC (%)	0.76	1.28	2.13	0.59	1.02	2.84
pH	0.58	0.42	1.59	0.31	0.08	1.36
OC (%)	0.32	0.16	1.32	0.29	0.30	1.24
TN (%)	0.31	0.02	1.36	0.15	0.01	1.21
SC2						
MC (%)	0.88	1.38	3.31	0.82	1.56	2.33
pH	0.68	0.37	1.83	0.38	0.55	1.26
OC (%)	0.48	0.12	1.64	0.07	0.18	0.95
TN (%)	0.50	0.01	1.50	0.06	0.02	1.02
SC3						
MC (%)	0.88	1.56	2.94	0.76	2.14	1.92
pH	0.81	0.38	2.31	0.73	0.46	1.92
OC (%)	0.71	0.22	2.03	0.65	0.28	1.67
TN (%)	0.79	0.02	2.18	0.81	0.02	2.28
SC4						
MC (%)	0.89	1.51	3.02	0.84	1.45	2.47
pH	0.72	0.43	1.94	0.64	0.52	1.66
OC (%)	0.71	0.23	1.96	0.72	0.23	1.85
TN (%)	0.75	0.02	2.09	0.76	0.03	2.02

[a] Coefficient of determination

[b] Root mean square error of prediction

[c] Residual prediction deviation (standard deviation/RMSEP)

SC1 (local samples); SC2 (regional samples); SC3 (national samples); SC4 (continental samples)

As for the model performed in 2014 (Table 5-2), results showed the best calibration model for MC was obtained with SC4 and SC2 (R^2 = 0.89 and 0.88, RPD = 3.02 and 3.31, respectively). The best model performance in the prediction set was also found in SC4 (R^2 = 0.84, RPD = 2.47) and SC2 (R^2 = 0.82, RPD = 2.33).

For OC and TN, the performance in cross-validation was better than in the prediction set in SC3 and SC4, with R^2>0.75 and RPD > 2.00 for TN; and R2 = 0.71 and RPD = 2.03 and 1.96 for OC. The accuracy levels of the prediction set were better in in SC4 for OC (R^2 = 0.72, RPD = 1.83) and SC3 for TN (R^2 =

0.81, RPD = 2.28). The results of prediction of TN and OC with the SC4 scenario are in agreement with those obtained previously by Kuang and Mouazen (2011c), using similar data set size with similar geographical variability.

5.2 On-line validation

In order to validate the on-line data of 2013 in two fields in Lincolnshire, UK, the four scenarios of calibration models generated were used to predict MC, OC, TN and pH based on soil spectra collected with the on-line soil sensor (Mouazen, 2006).

Table 5-3 On-line prediction of moisture content (MC), pH, organic carbon (OC), and total nitrogen (TN) obtained with four different scenarios. R2, RMSEP and RPD, were calculated for Field 1 (F1, MBHN01) and Field 2 (F2, OLD306) with vegetable production in Lincolnshire, UK.

	F1			F2		
	R^{2a}	RMSEP[b]	RPD[c]	R^{2a}	RMSEP[b]	RPD[c]
SC1						
MC (%)	0.95	0.79	2.52	0.85	0.78	2.59
pH	0.00	0.66	0.47	0.14	0.72	0.66
OC (%)	0.25	0.15	0.94	0.56	0.15	1.39
TN (%)	0.40	0.01	1.27	0.46	0.02	1.19
SC2						
MC (%)	0.69	1.44	1.39	0.85	0.87	2.32
pH	0.01	0.83	0.37	0.07	0.76	0.62
OC (%)	0.69	0.08	1.73	0.44	0.18	1.12
TN (%)	0.59	0.02	0.78	0.27	0.03	0.80
SC3						
MC (%)	0.77	1.34	1.49	0.78	0.98	2.07
pH	0.15	0.37	0.84	0.30	0.54	0.88
OC (%)	0.78	0.12	1.19	0.35	0.22	0.94
TN (%)	0.27	0.03	0.65	0.72	0.02	1.50
SC4						
MC (%)	0.91	0.71	2.80	0.83	0.84	2.39
pH	0.00	0.54	0.57	0.14	0.62	0.77
OC (%)	0.29	0.24	0.59	0.53	0.14	1.44
TN (%)	0.29	0.03	0.49	0.56	0.02	1.36

[a] Coefficient of determination

[b] Root mean square error of prediction

[c] Residual prediction deviation (standard deviation/RMSEP)

SC1 (local samples); SC2 (regional samples); SC3 (national samples); SC4 (continental samples)

Examining Table 5-3, results revealed that SC1 and SC4 performed very well for MC prediction (R^2 > 0.90 and RPD > 2.5), which is less performing as compared with previous studies (Mouazen et al., 2005) using the same sensor (RPD = 3.37; RMSEP = 0.025 $kgkg^{-1}$), but calibrated for individual field with arable crops in Belgium. Similar prediction accuracy was reported for MC by Kuang and Mouazen (2013), using continental calibration set spiked with local samples from new fields measured with the same on-line soil sensor (RPD > 2.76; RMSEP < 0.008 kg kg^{-1}).

Predictions were good for OC in F1 (MBHN01) with SC2 (R^2 = 0.69 and RPD = 1.73), whereas in F2 (OLD306) the best performed OC model was with SC4 (R^2 = 0.53 and RPD = 1.44). Less performance quality was obtained for TN, as compared to OC and MC in all scenarios. The best model performance for TN prediction was with SC2 and SC3 for F1 and F2, respectively.

In comparison with previous research using the same on-line soil sensor of Mouazen (2006), calibrations for OC and TN (Kuang and Mouazen, 2013), based on continental data set, spiked with samples from target fields (similar to SC4), provided better results (RPD > 1.86 and RMSE < 0.16 gkg^{-1} for TN and < 1.90 gkg^{-1} for OC), as compared to that of the current work. Poor on-line predictions for pH were reported for all scenarios (R^2 < 0.15 and RPD < 0.9 in F1; and R^2 < 0.30 and RPD < 0.9 in F2). This was disappointing results, as much better performance for pH prediction (R^2 = 0.78, RPD = 2.14 and RMSEP = 0.39) was reported by using the same sensor. Marín-González et al. (2013) reported much improved results based on continental data set spiked with samples from one field in Bedfordshire, UK. The disappointing results for pH prediction under both laboratory and on-line calibrations can be attributed to the different chemical composition of soils under vegetable crop production, as compared to those with arable crops (e.g. the case on good results reported by Marín-González et al., 2013). Further research is needed to understand the reason behind the poor pH prediction results.

The accuracy of the generated calibration models applied to the on-line validation measurements showed that the model performance thus depends on the property itself rather than scale or sample number. Therefore, it is not always correct to assume that field scale calibration model would give the best performance (Christy, 2008). Furthermore, these results have proven that the prediction performance also depends on the variability that differs between individual fields.

From the results of optimising the calibration of the on-line sensor to measure MC, pH, OC and TN it was decided to use different calibration scenarios to predict a property depending on the best accuracy obtained. The data generated with the on-line prediction were then used for further geostatistical analysis and modelling to produce MZ maps.

5.3 Maps of soil and crop properties

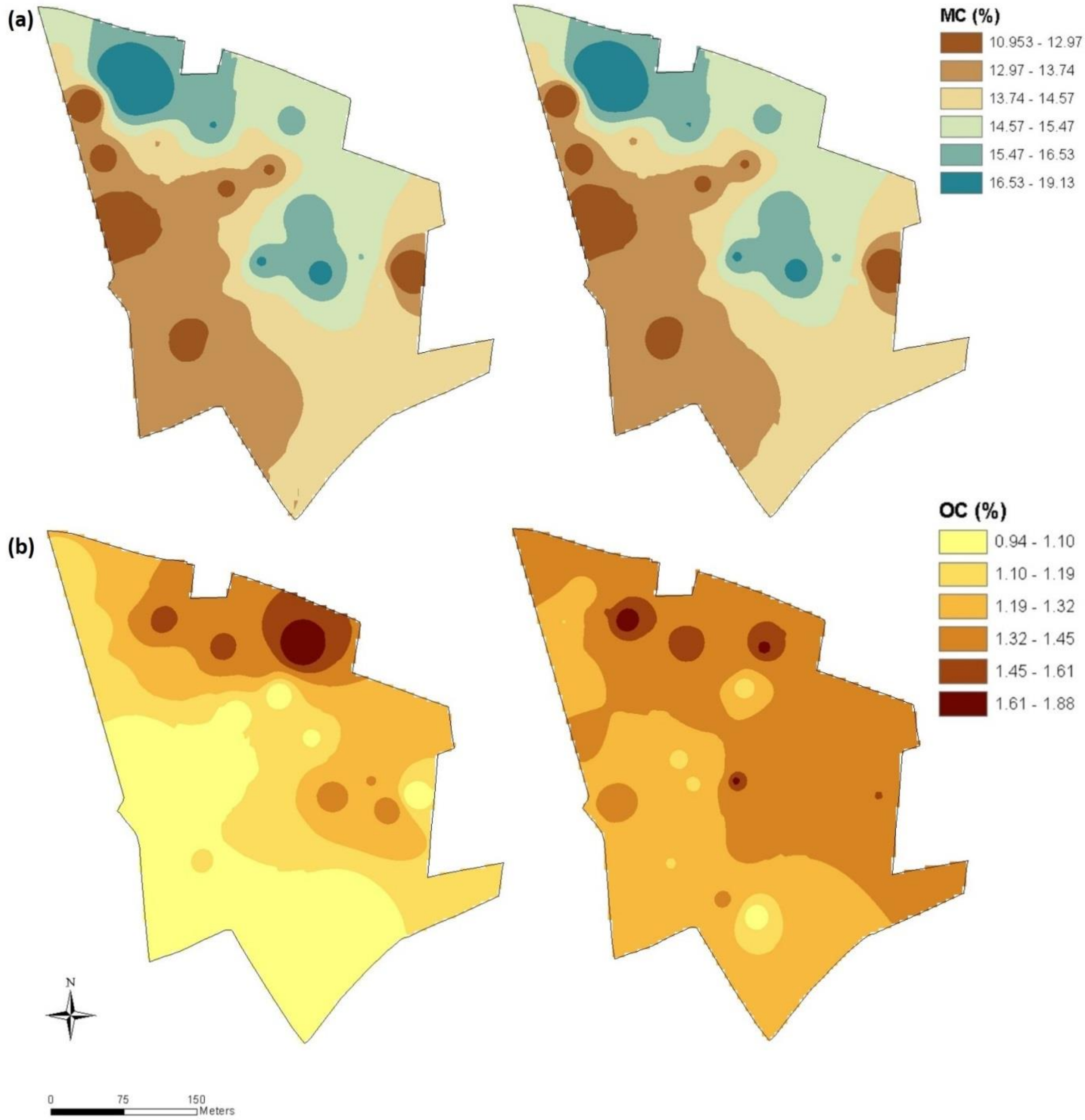
5.3.1 2013 experiment

Comparison maps

Figure 5-1 and Figure 5-2**Error! Reference source not found.** compare maps of on-line spectra-based predicted values and laboratory reference measured values for MC, OC, TN and pH in OLD306 and MBHN01 fields, respectively. In order to allow for meaningful comparisons between reference and on-line measured maps, the same number of classes (6 classes) was considered for all maps (Mouazen et al., 2007). A comparison between maps of measured and predicted soil properties investigated shows large spatial similarity, with high and low zones match almost perfectly for MC and OC, and similar for TN.

Very small spatial differences can be observed between maps developed with the referenced (laboratory) values and the corresponding maps developed with the on-line spectra. This proves the quality of the on-line measured spectra, showing a good sensor stability and robustness during the measurements (Kuang and Mouazen, 2013).

There is little literature about on-line prediction of properties without direct response in the NIR spectroscopy (Marín-González et. al, 2013), with soil pH being one of them. Mouazen et al. (2007) provided comparison between reference and on-line pH maps, showing a moderate similarity among them. A spatial similarity could also be found in pH maps in this study (Figure 5-2), although further research aiming at improving the quality of these maps are still needed.



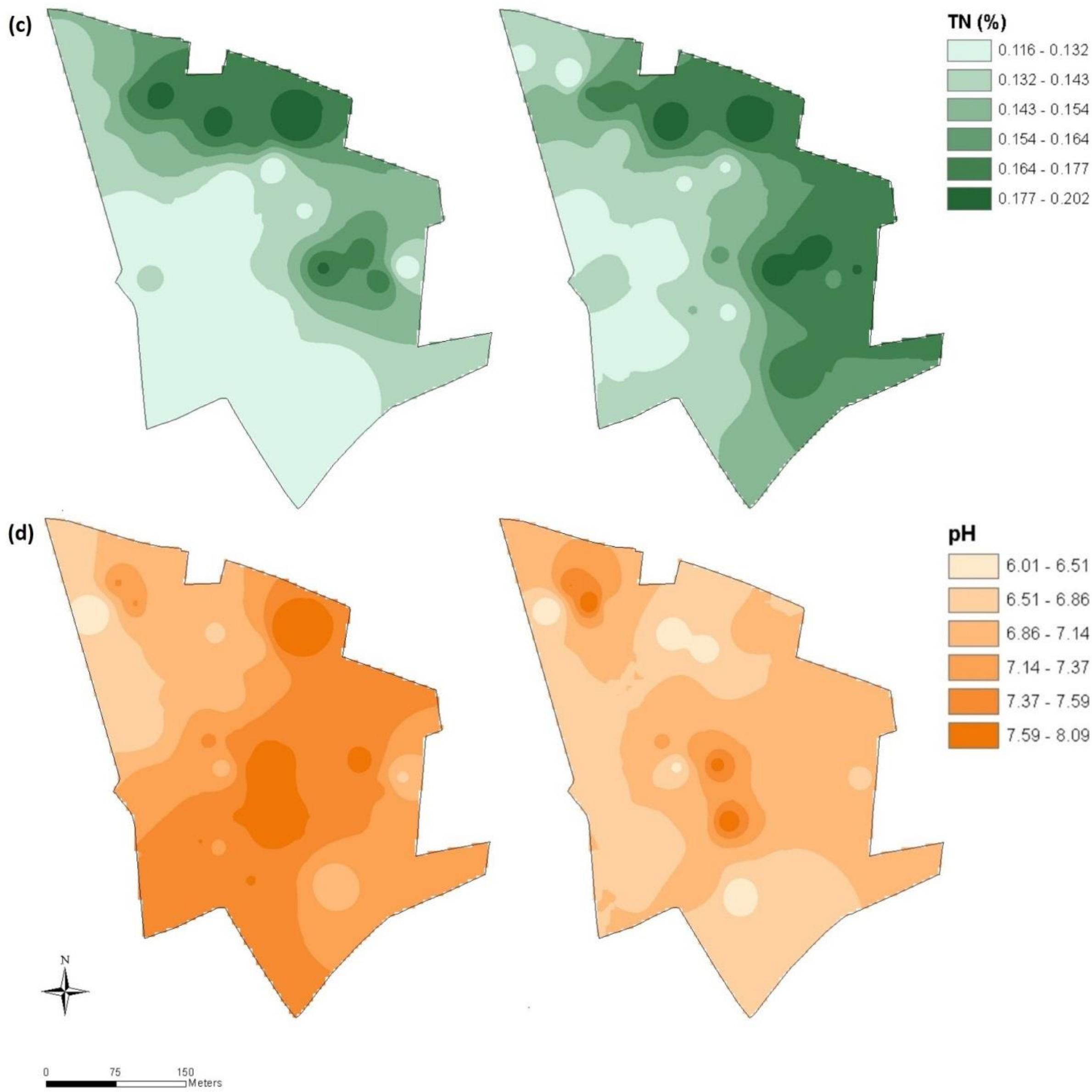


Figure 5-1 Comparison maps based on laboratory reference values (left) and on-line spectra predicted values (right) for moisture content (MC) (a), organic carbon (OC) (b), total nitrogen (TN) (c), and pH (d) in OLD306 field in Lincolnshire, UK.

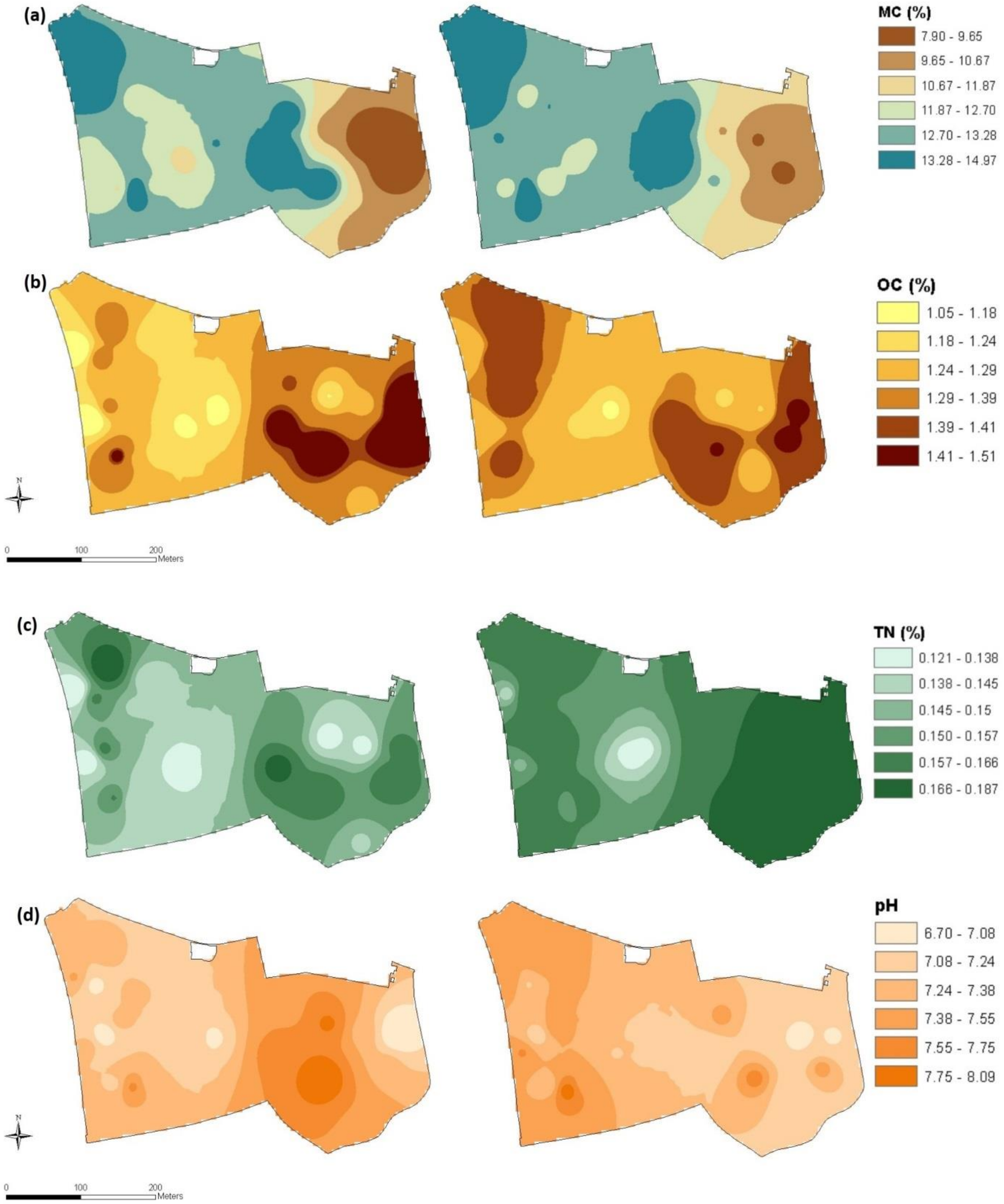


Figure 5-2 Comparison maps based on laboratory reference values (left) and on-line spectra predicted values (right) for moisture content (MC) (a), organic carbon (OC) (b), total nitrogen (TN) (c), and pH (d), in MBHN01 field in Lincolnshire, UK.

Full-data point maps

The semivariogram of the four properties analysed in both fields studied are summarised in Table 5-4. It is clearly shown that spherical as well as exponential and spherical semivariograms are the best fit for OLD306 and MBHN01 fields, respectively. Maps show high spatial variability of the four soil properties studied in OLD306 and MBHN01 (Figure 5-3 and Figure 5-4). This high variability encourages the need for on-line sensor for the characterisation of within field spatial variability of soil properties, as areas with different levels of concentration should be managed differently in precision agriculture, particularly for site-specific fertilisation.

Table 5-4 Semivariogram model parameters of moisture content (MC), total nitrogen (TN), organic carbon (OC), and pH used for mapping MBHN01 (a) and OLD306 (b) in Lincolnshire, UK.

Property	Model fit	Nugget (C_0)	Sill (C_0+C_1)	Range	Proportion (C_1/C_0+C_1)	Sum of square error (weighted)
MC[a]	Spherical	6.229	15.389	350.6	0.59523036	20198
TN	Spherical	0.006925	0.016775	400.2	0.58718331	6181.4
OC	Spherical	0.07388	0.21968	550	0.66369264	24750
pH	Spherical	0.956	2.308	371.3	0.58578856	14713
MC[b]	Exponential	2.272	11.972	7.853	0.81022386	2170.3
TN	Exponential	0	0.00981	5.788	1	1183.5
OC	Exponential	0.02375	0.13555	10.22	0.8247879	5394
pH	Spherical	0.8435	1.8225	34.73	0.53717421	510.9

A high similarity between OC and TN maps can be observed in both fields, which can be attributed to a large correlation that exist between these two properties in the soil (OLD306: R^2=0.91 and $p < 0.001$; MBHN01: R^2=0.69 and $p<0.001$). Moreover, comparing the maps generated with laboratory reference methods (Figure 5-1and Figure 5-2), produced with few measurement points with the full data point maps, based all on on-line measurement points (Figure 5-3 and Figure 5-4), one can be observe a more detailed characterisation of the field variation in the latter ones. This detailed information about the field variability is essential for accurate application of inputs in arable and vegetable crop fields.

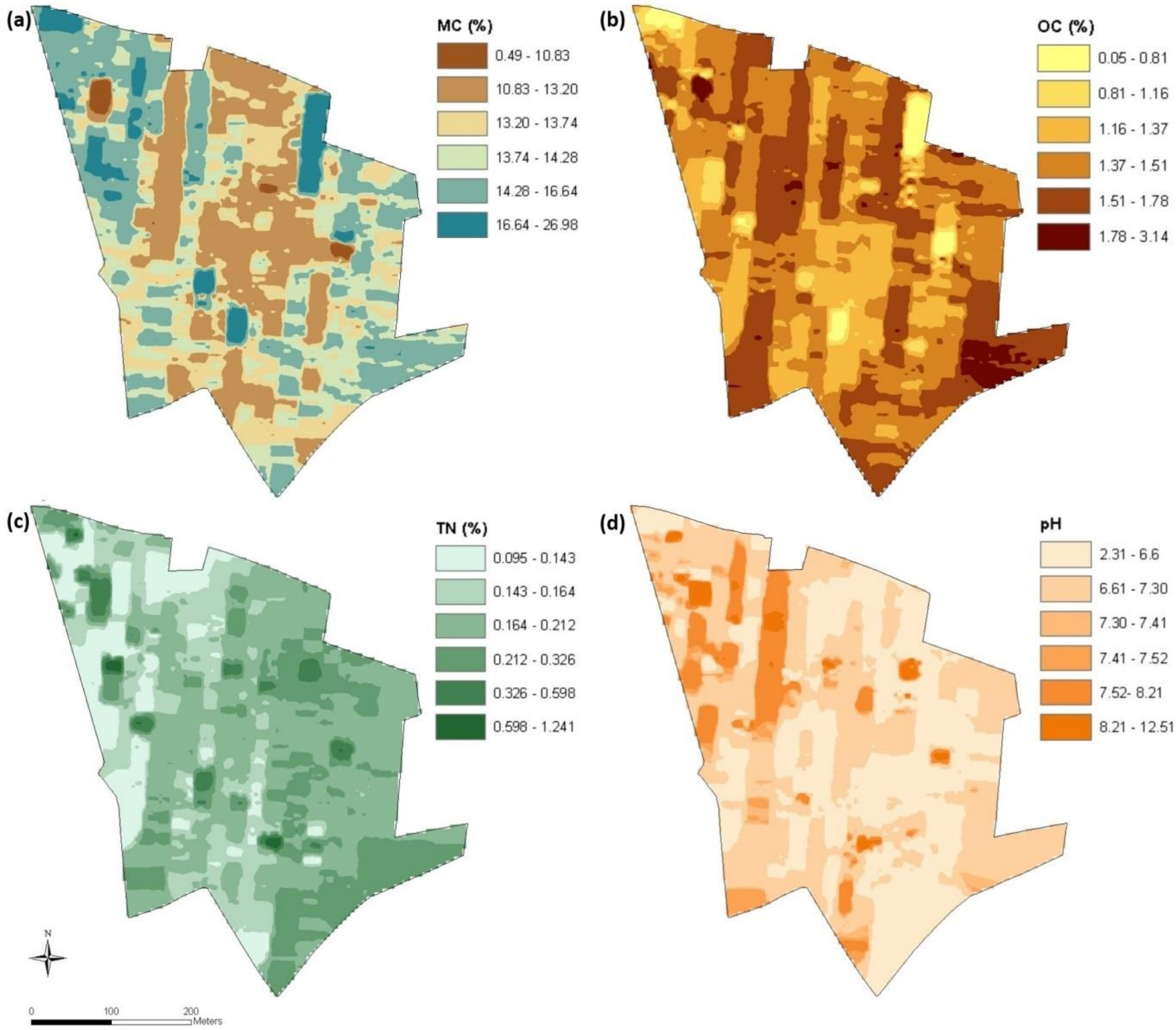


Figure 5-3 Full-data point maps of on-line predicted moisture content (MC) (a), organic carbon (b), total nitrogen (c), and pH (d) in OLD306 field in 2013.

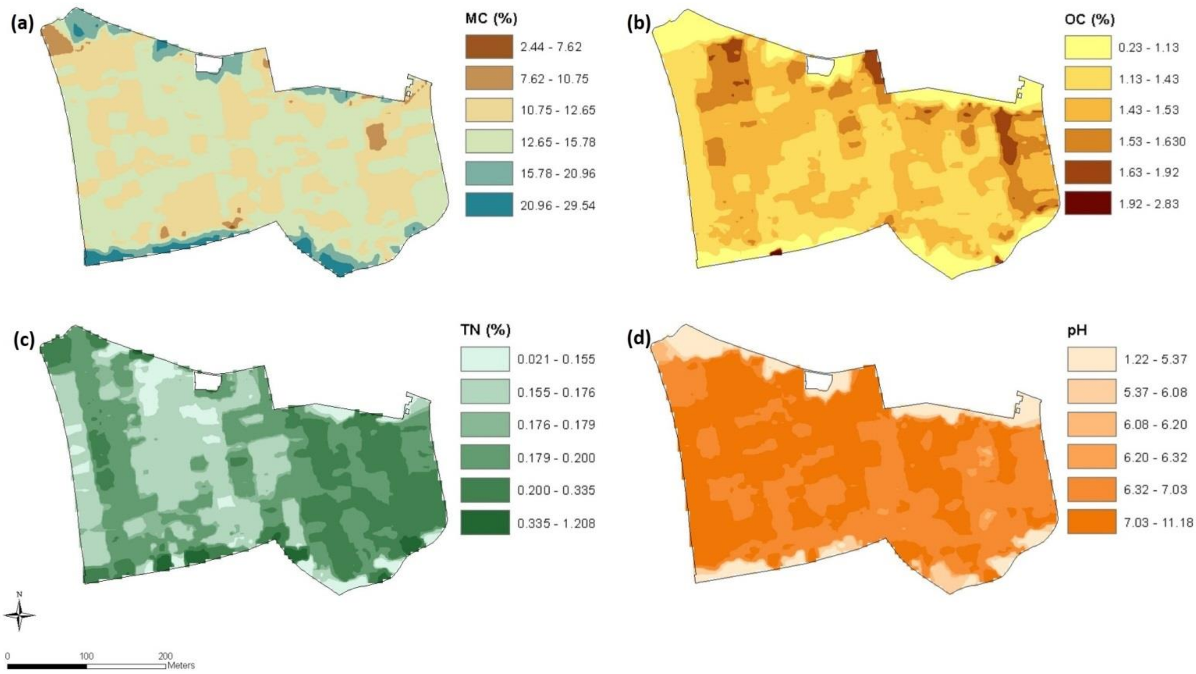


Figure 5-4 Full-data point maps of on-line predicted moisture content (MC) (a), organic carbon (b), total nitrogen (c), and pH (d) in MBHN01 field in 2013.

5.3.2 2014 experiment

Since validation maps were demonstrated successfully for 2013 experiment, it was decided to not repeat the same for 2014, and mapping only focused on the full-data point maps. The full point maps provided again very detailed maps for MC, OC, TN, and pH, in BWX102 (Figure 5-5), BWX103 (Figure 5-6), and BWX104 (Figure 5-7) fields. With these detailed maps, produced with on-line vis-NIR spectrophotometer-based sensor, it was assumed that better management decisions for N application should be achieved in the current work. Kuang and Mouazen (2013) also reported successful on-line vis-NIR maps for OC, TN and MC and recommended them for fertiliser recommendation application rather than conventional maps, based on laboratory analysis of best practice of one sample per hectare or one sample per field with several hectares.

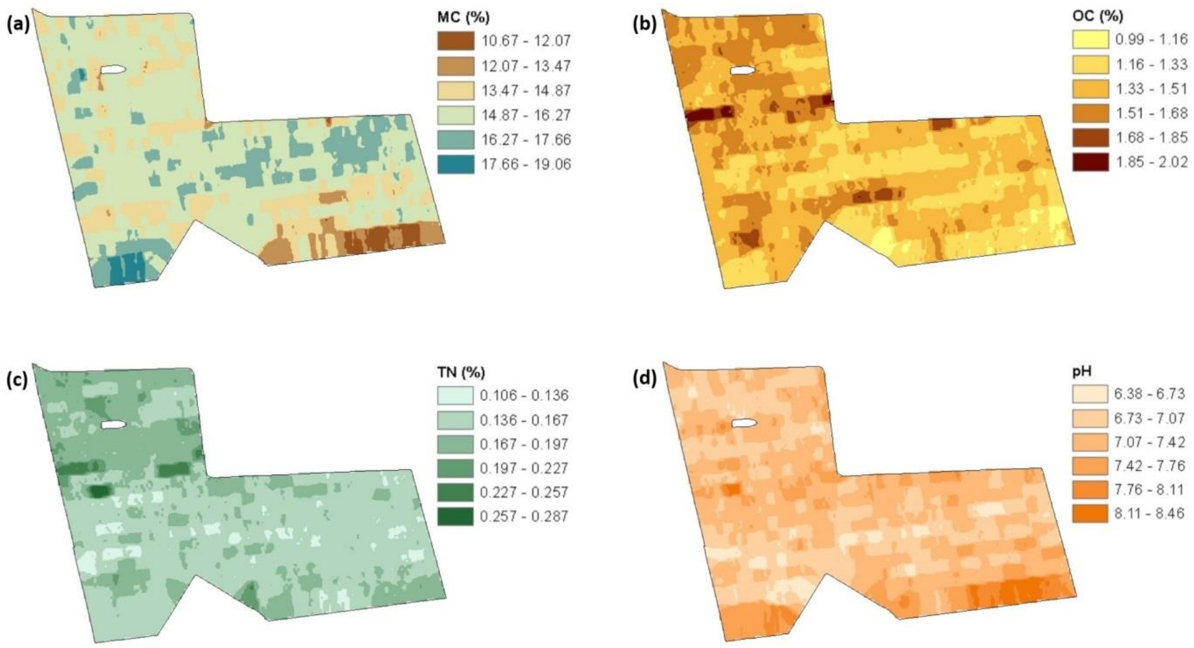


Figure 5-5 Full-data point maps of on-line predicted moisture content (MC) (a), organic carbon (b), total nitrogen (c), and pH (d) in BWX102 field of Beeswax farm in Lincolnshire, UK, in 2014.

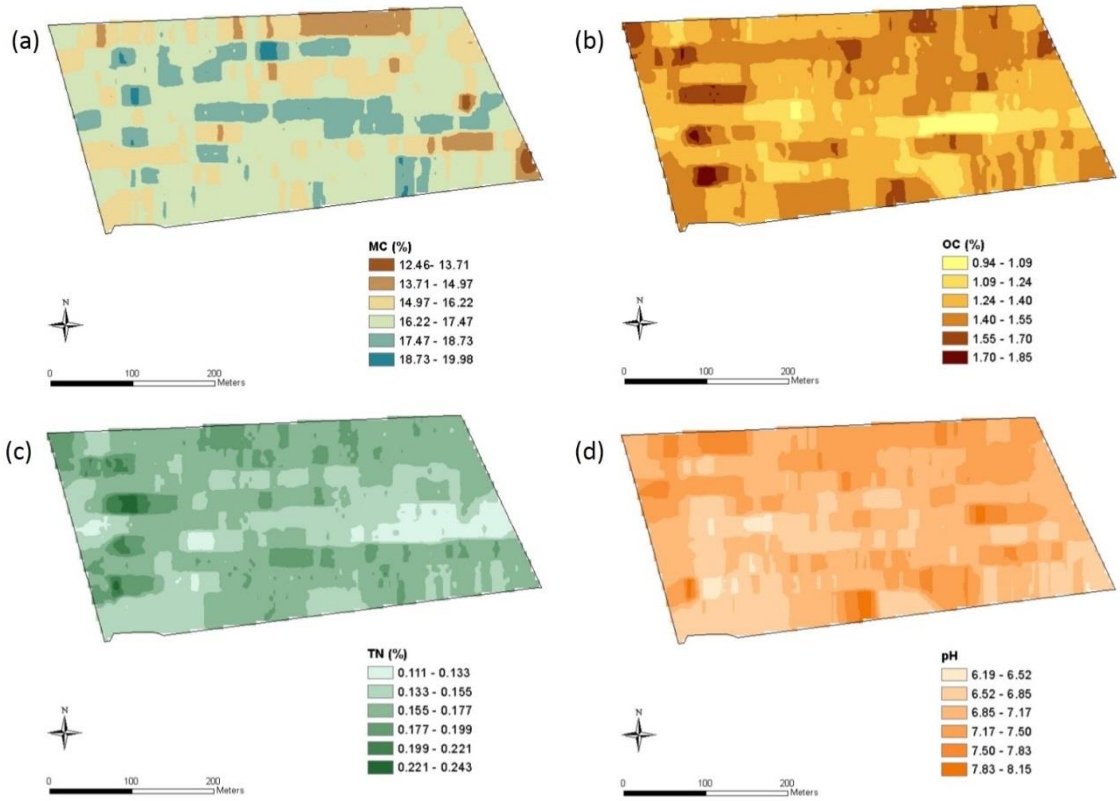


Figure 5-6 Full-data point maps of on-line predicted moisture content (MC) (a), organic carbon (b), total nitrogen (c), and pH (d) in BWX103 field of Beeswax farm in Lincolnshire, UK, in 2014.

As in 2013 experiment, Table 5-5 again shows that the most suitable semivariogram types for 2014 experiment are the spherical and exponential for all three studied fields.

5.4 Fertility maps

5.4.1 2013 experiment

Management zones delineation of OLD306 and MBHN01 were implemented by the method described in section 4.4.2. The UR application treated the whole field as a single MZ. The output maps after multivariate clustering for VR1 (a) and VR2 (b) of potential MZ are shown in Figure 5-8 and Figure 5-9, respectively. By examining the MZ maps of the two fields, one can observe the spatial variability, which confirms that different zones in the two fields have to be managed differently.

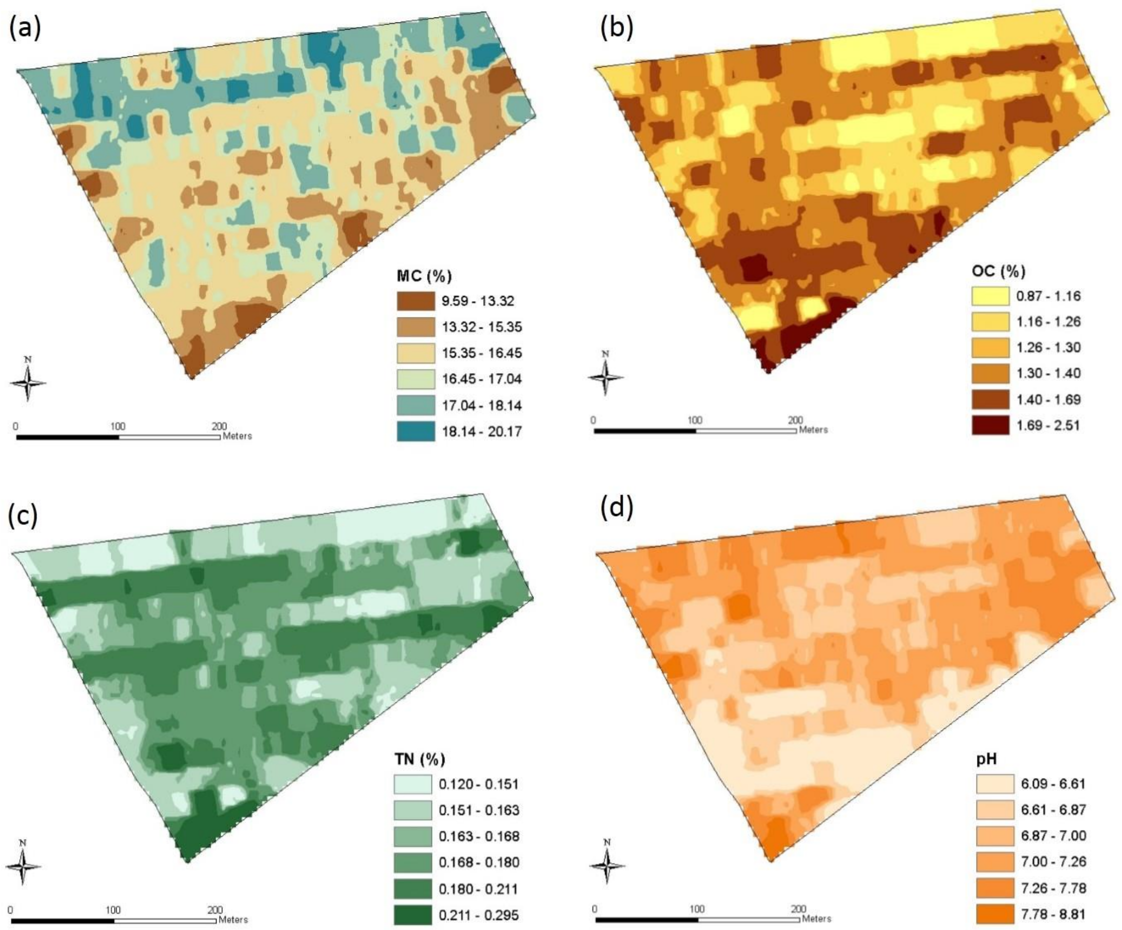


Figure 5-7 Full-data point maps of on-line predicted moisture content (MC) (a), organic carbon (b), total nitrogen (c), and pH (d) in BWX104 field of Beeswax farm in Lincolnshire, UK, in 2014.

This proves the necessity of treating the field as heterogeneous units and not as one unit (e.g. UR), by dividing the entire field area into zones, with each is managed differently accordingly to its needs (Halcro et al., 2013). One way to achieve that is by the integration of data on soil collected with the on-line vis-NIR spectrophotometer-based sensor with crop NDVI data measured with satellite imagery.

It is expected that due to the larger number of points considered during the clustering with VR2 input, that the number of classes in the management zones are bigger with VR2 concept than with VR1. The output of clustering showed three different classes in OLD306, by both clustering methods for VR1 and VR2, which does not support our assumption earlier (Figure 5-8).

Table 5-5 Semivariogram model parameters of moisture content (MC), total nitrogen (TN), organic carbon(OC) and pH used for mapping Beeswax Farm fields in Lincolnshire, UK.

Field_ID	Property	Model fit	Nugget (C_0)	Sill (C_0+C_1)	Range	Proportion (C_1/C_0+C_1)	Sum of square error (weighted)
BWX102	MC	Exponential	1.259	2.0701	32.94	0.39	347.5
	TN	Exponential	0.000149	0.000687	11.81	0.78	1845.5
	OC	Exponential	0.01243	0.03339	17.72	0.63	2428.8
	pH	Exponential	0.06802	0.14162	27.02	0.52	2068.1
BWX103	MC	Spherical	0.988	2.152	27.5	0.54	1421.3
	TN	Exponential	0.000256	0.000639	10.68	0.60	488.5
	OC	Spherical	0.0098	0.03084	33.19	0.68	6453.7
	pH	Spherical	0.1529	0.21728	352.1	0.30	2588.3
BWX104	MC	Exponential	1.746	3.047	13.88	0.43	790.7
	TN	Exponential	0.000357	0.001059	5.168	0.66	2658.9
	OC	Exponential	0.01417	0.04332	6.571	0.67	983.4
	pH	Exponential	0.08824	0.19524	14.69	0.55	1665.7

A total of 4 clusters were derived from VR2 and three for VR1 in MBHN01 (Figure 5-9). Working with similar concept of clustering to the current work but in an arable field, Halcro et al. (2013) reported a larger number of clusters obtained with VR2 (e.g. 5 clusters), as compared to the corresponding map for VR1 (e.g. three clusters). This again demonstrates the advantage of the high resolution sampling offered by the on-line soil sensor (>1500 sample per ha) and the satellite data.

Following cluster recommendations and developing the fertility maps for OLD306 and MBHN01 (Figure 5-8 and Figure 5-9, respectively), several observations can be made from the maps generated:

- VR2 maps showed more detailed zones with different fertility areas than VR1, particularly in MBHN01. The fertility map of VR1 in this field identifies three main areas (areas), whereas VR2 resulted in more than six management zones.

- Zones in VR2 are shown to represent the reality, while areas defined in VR1 maps tend to be more oval shaped and not practical for fertilisation machinery

(Cid-Garcia et al., 2013), due to the fewer amount of reference points used to generate such maps.

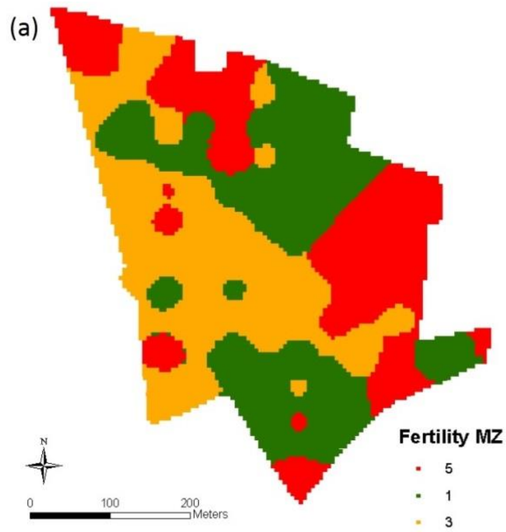


Figure 5-8 Output maps after k-mean clustering, identification and delineation of MZ of OLD306 field using VR1 (a) and VR2 (b).

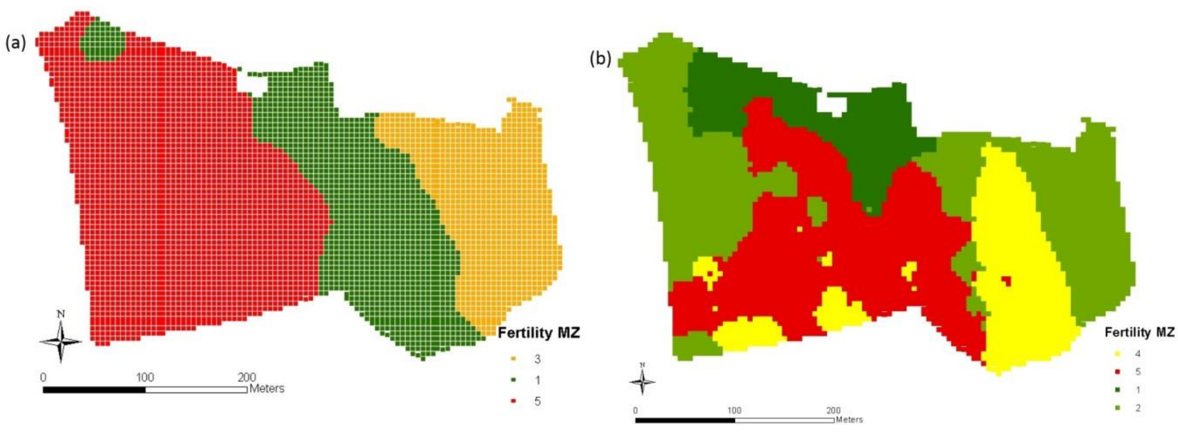


Figure 5-9 Output maps after k-mean clustering, identification and delineation of MZ of MBHN01 field using VR1 (a) and VR2 (b).

5.4.2 2014 experiment

Similar steps for creating MZ maps for 2013 were followed in 2014 in Beeswax farm fields (BWX102, and BWX103) to create the maps shown in Figure 5-10 and Figure 5-11, respectively. Comparing the maps generated with VR1 data and VR2 data, it can be observed that also the same number of classes was generated for both maps in BWX102; the variability of VR2 map are shown to be more detailed, which will allow for more precise fertiliser application. The MZ map of VR2 in BWX field was larger and more detailed as compared to the corresponding maps for VR1. This is additional clue to our correct assumption that the high resolution data obtained with the on-line sensor should lead to more detailed management (e.g. fertility) map. In this way, a better knowledge of nutrient scarcity in the field will lead to a better application within the field, i.e. just applying where is needed and avoiding over application and, hence, possible soil contamination (Morgan and Ess, 1997).

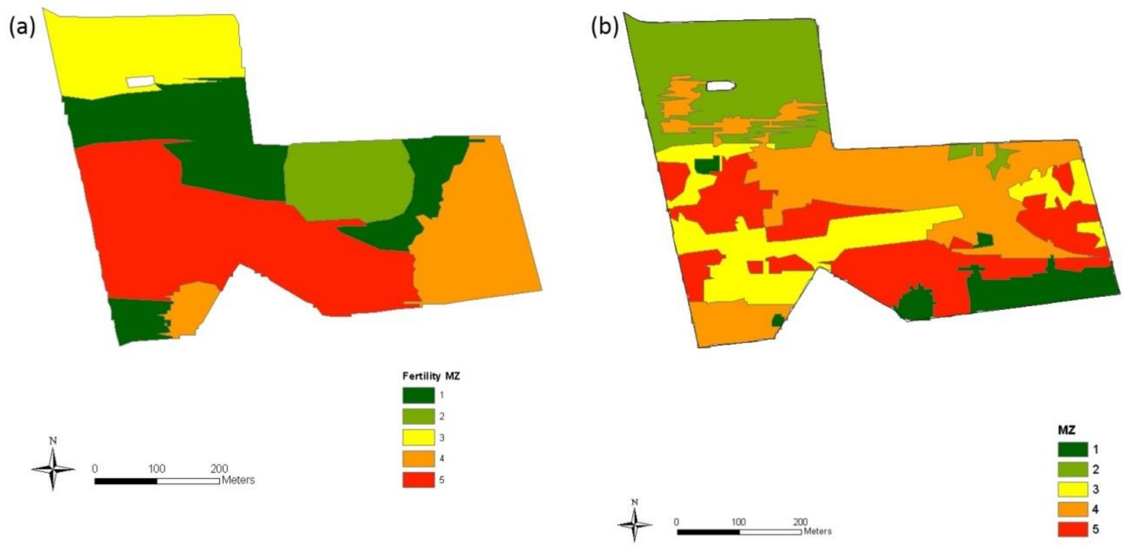


Figure 5-10 Output maps after k-mean clustering, identification and delineation of MZ of BWX102 field using VR1 (a) and VR2 (b).

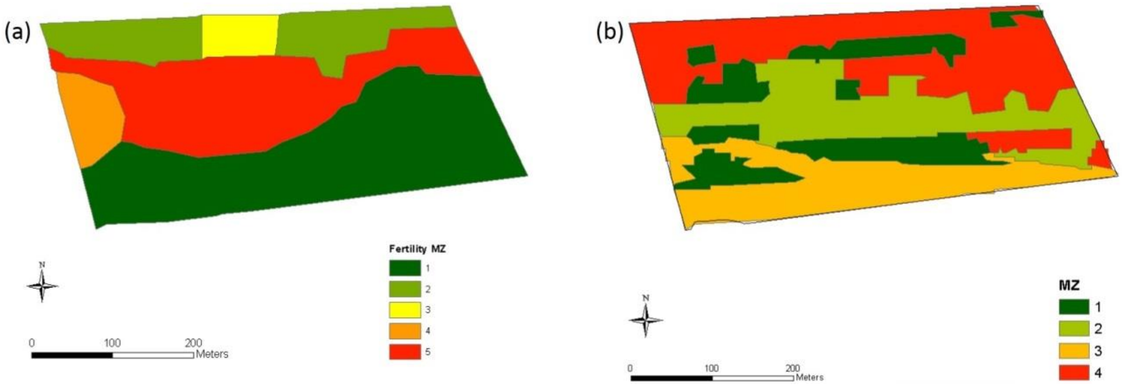


Figure 5-11 Output maps after k-mean clustering, identification and delineation of MZ of BWX103 field using VR1 (a) and VR2 (b).

Figure 5-12 shows the MZ map of BWX104 field developed with VR2 approach. Variable rate following classical zoning method (VR1) could not be done in this field, because this field became unavailable due to commercial contract that were out of hands to manage. However, on-line measurements with vis-NIR spectrophotometer were carried out at the time when the field was available and fertiliser recommendation maps with VR2 approach were made. The map indicates that this field should be subdivided into three different management zones, according to the fertility level. Then, fertiliser recommendations should be applied according to Table 4-5. Since no fertilisation experiment was implemented in 2014, further studies are needed to prove the MZ delineation was correct and effective for site specific nitrogen application.

5.5 Experimental plots output for 2013 measurement

5.5.1 Fertiliser input amount and costs

Fertiliser application was carried out following the three different treatments proposed in the trials and the rest of the field was treated as uniform rate (see section 4.4.1). The fertiliser used in this study was Yara Bella PRILLED N (34.5% N). The total amount and cost of fertiliser applied to each treatment trial are shown in Table 5-6**Error! Reference source not found.**. From these figures, it was possible to estimate the financial gain the farmer would have made for MBHN01 by employing VR2 over his usual UR or VR1 application for the whole field for this single year.

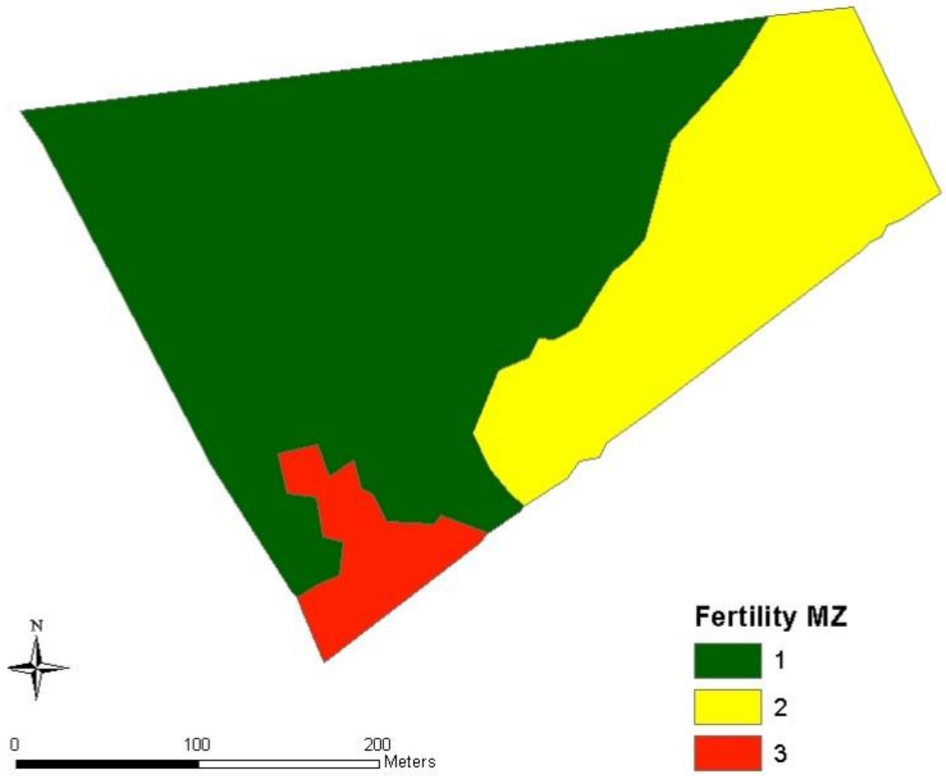


Figure 5-12 Output map after k-mean clustering, identification and delineation of MZ of BWX104 field using VR2.

By using the innovative MZ delineation approach based on the on-line vis-NIR sensor (VR2) and NDVI data, a total of £11.9 per hectare can be saved over the recommended UR and almost £34 per hectare as compared with the traditional VR1 approach. As for OLD306 field, calculations show average expenses of £215.8 per hectare when using VR1, that would be £29.2 less per hectare than using VR2 (£245.1/ha) or £17.3 less per hectare if using UR (£227.8/ha). The increase in fertiliser application with VR2 in this particular field might be attributed to the nutrients shortage, particularly in zone 5 (total N applied of 538.7 kg at a total cost of £423.16), which was with the poorest fertility index and occupied the largest area among the other clusters in the field (Table 5-6). Running similar fertilisation experiment in an arable field, Halcro et al. (2013) reported extra N application of £28 per ha, as compared to VR1 and smaller application of £3 per ha, as compared to the UR. The former extra figure of N use (£28 per ha) is comparable to that (£29.2 per ha) obtained with data for OLD306 field in this study (Table 5-6). Although VR2 consumed more N fertiliser than VR1 in Halcro et al. (2013), work extra margin of £29 per ha was reported for VR2, as compared to VR1, which indicates that even if more N fertiliser is applied the extra yield due to the precision application can compensate for the extra cost, so that the final balance is positive in VR2 favour.

Table 5-6 Amount of nitrogen fertiliser applied and associated costs of three different treatments of uniform rate (UR) traditional variable rate (VR1) and innovative variable rate (VR2) in two fields in Lincolnshire in 2013 season.

ID	Treatment	MZ	Area (ha)	N applied (kg)	N (kg/ha)	No. bag of product	Tonnes of product (t)	Product price range (£/t)	Total cost (£)	Cost (£/ha)
MBHN01	UR	n/a	1.92	556.1	290.0	2.69	1.61	271	436.82	**227.8**
	VR1	1	0.46	107.5	232.0	0.52	0.31	271	84.41	
		3	0.09	26.4	290.0	0.13	0.08	271	20.78	
		5	1.40	488.6	348.0	2.36	1.42	271	383.79	
		TOTAL	*1.96*	*622.5*	*317.9*	*3.01*	*1.80*	*271*	*488.98*	**249.7**
	VR2	1	0.26	59.6	232.0	0.29	0.17	271	46.80	
		2	0.74	195.0	262.2	0.94	0.57	271	153.21	
		4	0.29	91.1	319.0	0.44	0.26	271	71.56	
		5	0.62	177.3	287.5	0.86	0.51	271	139.30	
		TOTAL	*1.90*	*523.1*	*274.8*	*2.53*	*1.52*	*271*	*410.88*	**215.9**
OLD306	UR	n/a	2.58	749.6	290.0	3.62	2.17	271	588.81	**227.8**
	VR1	1	0.99	230.0	232.0	1.11	0.67	271	180.63	
		3	1.48	429.4	290.0	2.07	1.24	271	337.32	
		5	0.27	94.4	348.0	0.46	0.27	271	74.13	
		TOTAL	*2.74*	*753.8*	*274.8*	*3.64*	*2.18*	*271*	*592.09*	**215.8**
	VR2	1	0.41	95.2	232.0	0.46	0.28	271	74.79	
		3	1.04	302.1	290.0	1.46	0.88	271	237.27	
		5	1.55	538.7	348.0	2.60	1.56	271	423.16	
		TOTAL	*3.00*	*936.0*	*312.0*	*4.52*	*2.71*	*271*	*735.22*	**245.1**

These margin figures do not take into account the cost of surveys, labour, petrol, and equipment. By using VR2 approach, more detailed data is made available to produce more precise fertility maps; hence a better fertiliser application and yield uniformity is expected, as compared to both traditional applications of the UR and VR1. Halcro et al (2013) proved the use of VR2 in arable crops will contribute to deliver better profit to farmers (about £50 per ha), since this approach delivered a larger yield increase over the UR and VR1 together. This will lead into allow growers to more accurate target inputs whilst reducing waste and environmental impact.

These results encourage the recommendation on data fusion of crop and soil properties measured, respectively, with satellite imagery and the on-line vis-NIR soil sensor, for a better delineation of MZ for site-specific nitrogen fertilisation application.

5.5.2 Crop response for 2013 measurement

After fertiliser application, crop quality measurements of cauliflower (*Brassica oleracea* var. *botrytis*) including leave number, plant height and curd size were carried out before harvest at least three times in OLD306 and two times in MBHN01, to follow the development of the crop through the entire growing period and the response of crops to different fertiliser applications. The first measurement of crop responses was carried out in the second week of August in both fields, and followed with two more measurements in August and September in OLD306 field. The results of height, number of leaves and crown are shown in Table 5-7 for MBHN01 field, with a total of two measurements, since the second measurement in this field was done just for curd diameter; and Table 5-8 for OLD306, with three measurements before harvest. Detailed frequency distribution graphs of these measurements can be found in Appendix C. Examining the SD, one can observe that variations in height and crown diameter in particular are the smallest with VR2 plots as, compared to both UR and VR1, which confirms that crop yield in VR2 treatment is more homogeneous, which is the main market requirement in cauliflower production. Producers will get more benefit for more homogeneous products.

Curd diameter is the most important parameter to take into account in this crop survey, since is the edible portion and the final product to be packed and delivered to the supermarket (Beale, 2011). According to Produce World Ltd., the harvesting of cauliflowers represents approximately 50 per cent of the cost of production. Any savings on harvest by enhancing curd homogeneity will have a major impact on the profitability of the crop and will reduce waste and the need to place surplus product to cold store or to sell it to open market at a low price. More accurate knowledge of harvest profile will allow the marketing function to anticipate and react to the crop situation.

Table 5-7 Statistics from the cauliflower survey conducted in MBHN01 field, 2013.

Treatment	Height (cm)				No. Leaves				Crown Ø (cm)			
	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
UR	13.0	38.0	25.8	5.4	10.0	21.0	15.2	2.1	33.0	81.0	64.7	9.7
VR1	14.0	38.0	25.9	5.1	8.0	20.0	14.7	2.6	30.0	85.0	65.0	9.4
VR2	15.0	40.0	26.1	5.1	8.0	21.0	14.5	2.6	44.0	85.0	66.2	8.4

The measurement of cauliflower curd was done when the curd was initiated and the plant was carefully dissection. Figure 5-13 shows the normal distribution curve of two times curd measurements for MBHN01 field. Taking into account that curd optimum size to be marketable has to be around 12-15 cm, the percentage of the plants measured in September (1st measurement) that satisfies this requirement was 26.8%, 24.6% and 17.6%, with VR2, VR1 and UR, respectively. The importance of applying the right amount of nitrogen fertiliser in crops at first growing stages is vital to the development of the plant. In this case, it is proven that using VR2 approach is more beneficial than VR1 or UR. However, in the second time of crop measurement in October (close to crop end), percentages of cauliflower curds meeting the market requirements were more even among treatments (43.8% in VR2, 47.3% in VR1, and 43.7% in UR).

Curd measurements of OLD306 are shown in Figure 5-14, where only one time was possible to do the measurement before harvesting due to time pressure on the farmer side to harvest the crop. As it can be observed that in the normal distribution curve, the early growth stage of the curd at this measurement time cannot provide solid estimation of the final output. The measurement was done too early to draw robust conclusions, as the percentage of plants that produced a marketable head ranged from 2 to almost 10 per cent (VR2 = 2.5%, while in VR1 and UR were 4.5% and 9.2%, respectively). In this case VR2 was not performing as good as in MBHN01. Probably the main reason for not finding a major improvement using VR2 approach was the early measurement (Table 4-4); where no second measurement was allowed due to time pressure to harvest the crop.

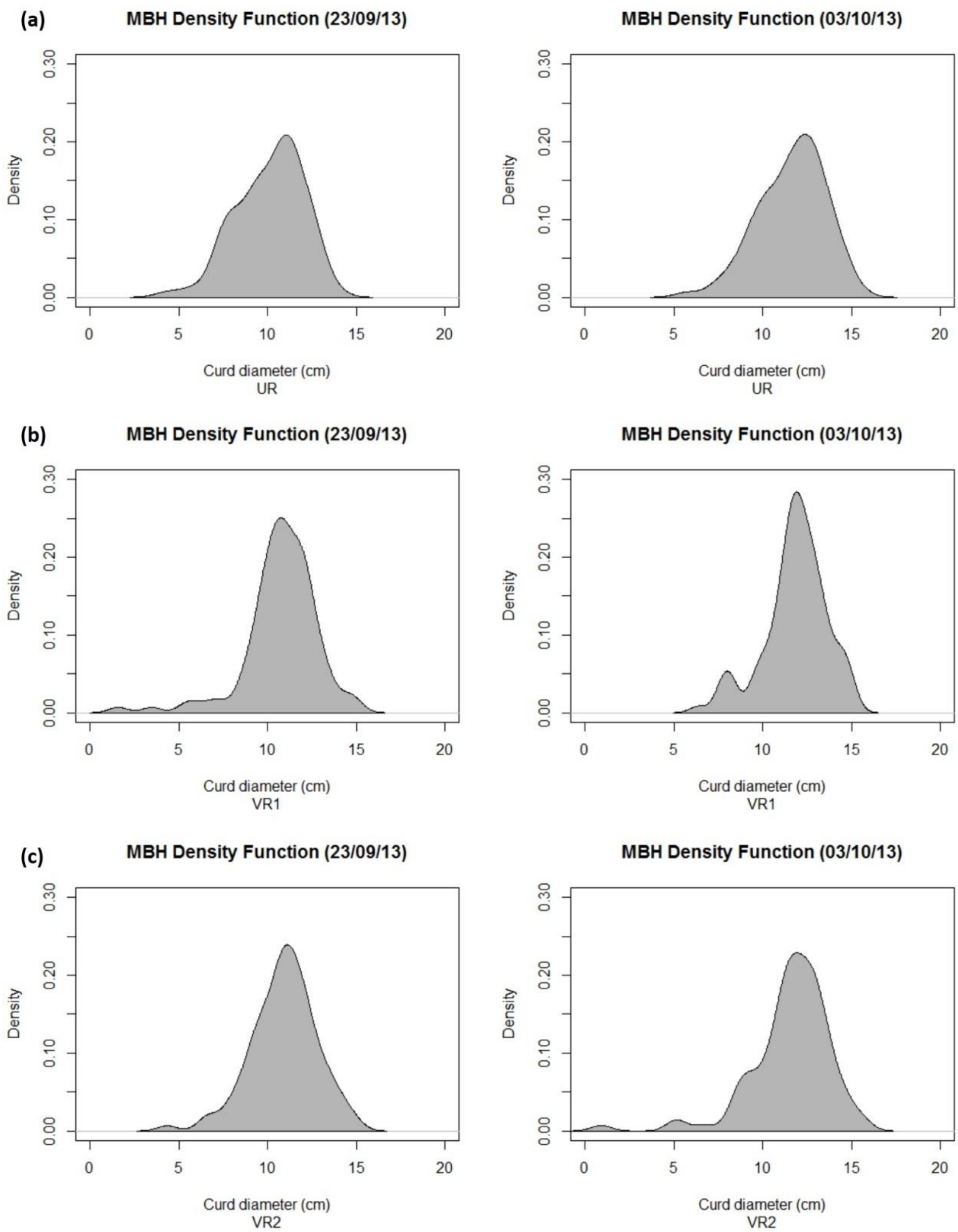


Figure 5-13 Normal distribution curve of cauliflower curd size in measurement 1 (first time collecting data) (left) and measurement 2 (second time collecting data) (right) for the different treatments applied: UR (a), VR1 (b), and VR2 (c); in the field MBHN01.

Table 5-8 Summary of statistics for cauliflower survey performed in OLD306 during summer 2013.

Measure	Treatment	Height (cm)				No. Leaves				Crown Ø (cm)			
		Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
1	UR	15.0	40.0	26.6	5.5	8.0	16.0	12.0	1.9	20.0	70.0	45.7	10.3
	VR1	12.0	44.0	26.6	6.5	7.0	19.0	11.7	2.1	26.0	65.0	43.7	8.3
	VR2	12.0	38.0	25.8	5.8	7.0	15.0	11.5	1.9	23.0	65.0	41.6	10.3
2	UR	23.0	60.0	40.2	8.3	10.0	22.0	15.7	2.8	30.0	80.0	55.9	11.6
	VR1	18.0	55.0	39.7	7.3	7.0	23.0	15.8	2.6	22.0	85.0	56.9	10.9
	VR2	17.0	58.0	39.6	8.2	9.0	21.0	15.5	2.4	20.0	85.0	54.6	14.1
3	UR	44.0	70.0	55.2	7.2	12.0	20.0	16.3	2.0	45.0	78.0	64.2	10.0
	VR1	35.0	77.0	57.3	8.6	10.0	22.0	17.0	2.8	36.0	94.0	73.7	11.7
	VR2	30.0	75.0	56.4	10.8	13.0	20.0	17.0	2.1	36.0	80.0	64.4	13.0

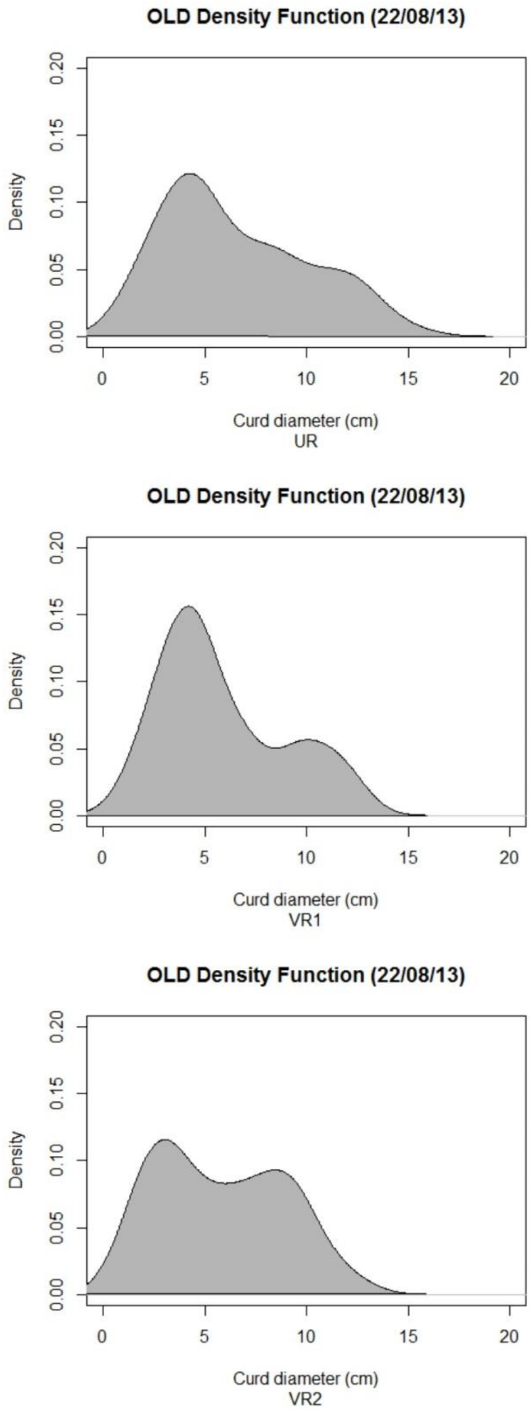


Figure 5-14 Normal distribution curve of cauliflower curd size with the data collected in OLD306 before harvesting, summer 2013: UR (top), VR1 (centre), and VR2 (bottom).

5.6 Virtual results of 2014 measurements

The costs of fertility decisions are affected by several factors, namely, product costs, the formulation (percent of nitrogen in the product) and the rate at which is applied. In this study, the fertiliser product chosen for these virtual calculations is the same used for 2013 experiments (Yara Bela PRILLED N - 34.5% N). The product price range was taken from June 2014 average fertiliser prices for ammonium nitrate (AN) (UK-bags, containing 600 kg of product) of 34.5% N. The price was rated at £254 per tonne for June 2014. The total amount of pounds that potentially would have been spent on each field for three different treatments (i.e. UR, VR1, and VR2) is shown in Table 5-9. However, treatment following VR1 approach could not be done in BWX104, since soil samples could not be hand collected due to industrial decisions. Comparisons could only be done between VR2 and UR in this field.

In one out of three fields, VR2 would result in increase the cost of N application, as compared to VR1 and UR application. In field BWX102, the farmer would spend £24.9 and £9.9 per hectare more if applying N fertiliser recommended according to VR2 (£238.4/ha) in comparison with UR (£213.5/ha) and VR1 (£228.5/ha), respectively. Although VR2 seems to be more expensive treatment in this field, this may be due to poor management of N in previous years so the soil needs an extra input. Nevertheless, the application of less N fertiliser than the amount that the field needs for an appropriate crop growth, will lead to economic losses, since the crop might not reach the quality standards to be marketable. The key is to apply the right amount of fertiliser precisely where is needed, so maybe this particular field was underachieved because of the lack of enough nutrients to grow the crop and meet the right marketable standards.

In the other two fields BWX103 and BWX104, improvement on cost saving was observed with VR2 (Table 5-9). For BWX103, the cost of N application with VR2 is £197.9/ha, which is £15.6 less than if UR is to be recommended. Similar results for BWX104 showed that applying VR2 will save the farmer £65.1 per hectare in comparison to UR (£213.5/ha).

Optimal delineation method of MZ using VR2 for nitrogen fertiliser recommendation proved to be more beneficial than using UR in both BWX103 and BWX104 fields. A high cost of application can be observed with UR application. Maleki et al. (2008) reported satisfactory implementation of phosphorus fertiliser applications in a corn field by using vis-NIR VR technique. Halcro et al. (2013) successfully showed the potential increase of oil seed rape yield by delineating MZ using proximal sensors, compared to VR1 and UR. In this work, it is not assumed a tax or subsidy imposed on the leaching of nitrogen fertiliser in case of applying too much, so this must be considered in future research.

In partial budgeting, net return due to a change in a farming system equals gains minus losses resulting from the change (Wang et al., 2003). In this study, potential gains of VR2 resulted from the increased revenue due to reduced costs from lower/better implementation of N application rates is shown to be possible, as compared to UR, but not in all case studies. However, increase in application cost due to the use of the on-line vis-NIR spectrophotometer has to be taken into account is future research. Also, the input-output cost-benefit analysis needs to be carried out for more fields and for several cropping seasons to conclude whether or not the use of VR2 approach will lead to increase farming efficiency sustainably in vegetable crop production, which was proved to be the case in arable crops (Halcro et al., 2013).

Table 5-9 Virtual fertiliser application costs in Beeswax fields for 2014 season using uniform rate (UR), variable rate 1 (VR1), and variable rate 2 (VR2).

ID	Treatment	MZ	Area (ha)	N applied (kg)	N (kg/ha)	No. bag of product	Tonnes of product (t)	Product price range (£/t)	Total cost (£)	Cost (£/ha)
BWX102	UR	n/a	24.56	7122.1	290.0	34.41	20.64	254	5243.52	**213.5**
	VR1	1	5.92	858.1	145.0	4.15	2.49	254	631.78	
		2	2.44	531.2	217.5	2.57	1.54	254	391.05	
		3	3.51	1017.2	290.0	4.91	2.95	254	748.87	
		4	4.23	1532.0	362.5	7.40	4.44	254	1127.92	
		5	8.47	3682.3	435.0	17.79	10.67	254	2711.01	
		TOTAL	*24.56*	*7620.7*	*310.3*	*36.82*	*22.09*	*254*	*5610.64*	**228.5**
	VR2	1	1.71	247.4	145.0	1.20	0.72	254	182.14	
		2	5.32	1156.4	217.5	5.59	3.35	254	851.39	
		3	4.22	1224.0	290.0	5.91	3.55	254	901.14	
		4	7.35	2665.6	362.5	12.88	7.73	254	1962.50	
		5	5.94	2582.0	435.0	12.85	7.71	254	1957.71	
		TOTAL	*24.56*	*7875.4*	*320.7*	*38.42*	*23.05*	*254*	*5854.88*	**238.4**
BWX103	UR	n/a	12.36	3584.0	290.0	17.31	10.39	254	2638.65	**213.5**
	VR1	1	5.43	787.4	145.0	3.80	2.28	254	579.73	
		2	1.98	429.8	217.5	2.08	1.25	254	316.40	
		3	0.47	137.6	290.0	0.66	0.40	254	101.31	
		4	0.65	237.1	362.5	1.15	0.69	254	174.59	
		5	3.82	1663.2	435.0	8.03	4.82	254	1224.51	
		TOTAL	*12.36*	*3255.1*	*263.4*	*15.73*	*9.44*	*254*	*2396.54*	**193.9**
	VR2	1	2.41	349.5	145.0	1.69	1.01	254	257.28	
		2	3.02	656.9	217.5	3.17	1.90	254	483.59	
		3	2.71	785.9	290.0	3.80	2.28	254	578.60	
		4	4.22	1529.8	362.5	7.39	4.43	254	1126.25	
		TOTAL	*12.36*	*3322.0*	*268.8*	*16.05*	*9.63*	*254*	*2445.73*	**197.9**
BWX104	UR	n/a	9.78	2834.8	290.0	13.69	8.22	254	2087.10	**213.5**
	VR2	1	6.49	941.7	145.0	4.55	2.73	254	693.27	
		2	2.75	796.2	290.0	3.85	2.31	254	586.16	
		3	0.54	233.1	435.0	1.13	0.68	254	171.59	
		TOTAL	*9.78*	*1970.9*	*201.6*	*9.52*	*5.71*	*254*	*1451.03*	**148.4**

CHAPTER 6. CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This study presents the potential of using on-line visible (Vis) and near-infrared (NIR) spectroscopy to predict soil properties within vegetable crops, with a rapid, non-destructive, timely and cost-effective new methodology for optimal site-specific nitrogen fertiliser application.

In order to evaluate the accuracy of an on-line vis-NIR sensor to refine nitrogen fertiliser applications in cauliflower crop fields, soil MC, OC, TN, and pH were measured to generate management zone maps and create more accurate N fertiliser recommendation maps. From the results obtained, the following general conclusions can be made:

- Variable rate N fertiliser application based on the new VR2 approach provided only slightly improved results of the crop physiological parameters than using UR or traditional VR1.
- Comparison of MC, OC, TN, and pH maps between chemically measured and on-line predicted values in OLD306 and MBHN01 fields, showed similar spatial variability, which demonstrates the potential of the vis-NIR sensor to maps key soil fertility parameters.
- In order to compare the efficiency of using VR2 instead of UR or traditional VR1, a larger change in N fertiliser rate should be applied if a clear crop response is to be recorded in the future. This is the reason why in 2014 experiment, the N rate was proposed to vary between ±50% kg/ha, based DEFRA recommendations.
- Results also showed remarkable spatial variability in soil fertility in the studied field with vegetable crop production, suggesting that different zones in a field have to be managed differently. This proves the necessity of treating the fields as heterogeneous unit and not as a whole (UR).

In order to evaluate the accuracy of vis-NIR calibration models for the prediction of soil MC, pH, OC and TN in vegetable crop fields, four initial calibration model scenarios for each soil properties have been generated with different number of samples having different scale of variability. From the results obtained in each case scenario and for the on-line validation in two fields, the following conclusions can be drawn:

- In general, the best performance of calibration models in cross-validation and prediction was obtained with SC3 (national samples) and SC4 (continental samples) of the four soil properties. These two scenarios have resulted not only in higher R^2 and RPD values, but also in larger RMSEP. This was attributed to the wider range and SD of the corresponding two sample sets.
- It is not always correct to assume that field scale models are the best performing. As shown in this study, calibration models using several fields with heterogeneous data can provide greater accuracy than individual field calibration models.
- The model performance depends on the property itself. For this, it is recommended to use the best performing calibration model for each soil property studied.

In order to evaluate the economic benefits of applying nitrogen fertiliser in vegetable crop fields, three approaches where compared, namely, UR, traditional VR1, and vis-NIR soil sensor-based VR2 application. Costs of fertiliser application per hectare for each treatment were analysed for 2013 and 2014 fields, and crop response analysis were determined for two fields studied in 2013 only. From the results obtained in each treatment, it can be concluded that:

- The innovative approach (VR2), will result cost saving of £11.9 per ha in MBHN01 field in comparison with UR. On the contrary, for OLD306 field, VR2 will be more expensive than UR by £17.3 per hectare. This could be attributed to a nutrient shortage within the field, particularly in the area classified as the poorest fertility, which represented the largest area in this field.

- Crop response to these fertility application treatments proved to be correlated with fertiliser application treatments. In MBHN01 the percentage of cauliflowers reaching the optimum marketable size was higher in VR2 plots, as compared to both UR and VR1. However, due to the fact that measurement of crop response in OLD306 was done too early (only 2-10% of plants reached the marketable size), and no other measurement was allowed, no robust conclusions was possible to make, although the cauliflower cruds reaching the marketable standards was higher in the UR plots.
- In Beeswax Farm fields, virtual results of fertiliser applications under different treatments were calculated in three fields. In general, the use of the new VR2 approach proved to save N fertiliser cost in two out of three fields, as compared to UR. The potential N fertiliser cost in VR2 in BWX102 field was higher (£ 238.4 per ha) in comparison with UR (£213.5 per ha) and VR1 (£228.5 per ha). For BWX103 field, VR applications were a better choice (VR1 = £193.9 per ha; VR2 = £197.9 per ha) than using UR (£213.5 per ha). For BWX104 field, comparing costs between VR2 and UR showed considerable saving to the former if applying VR2 (£148.4 per ha), as compared to the UR (£213.5 per ha), which is a saving up to £65 per hectare in the N fertiliser costs.

Although, the current work shows the potential of the new VR2 for managing N fertiliser more efficiently than both VR1 and UR, further work is needed to confirm this is the case. The input-output cost-benefit analysis needs to be carried out for more fields and for several cropping seasons to conclude whether or not the use of VR2 approach will lead to increase farming efficiency sustainably in vegetable crop production, which was proved to be the case in arable crops.

6.2 Future work

The application of on-line vis-NIR spectroscopy and data fusion modelling, implemented in the current work as a tool for site-specific nitrogen fertiliser management necessitates the following future works:

1. There is a need to develop calibration models for other soil properties e.g. soil P, K, Ca, Mg, pH and CEC , to enable the use of the on-line vis-NIR sensor (Mouazen, 2006) for the measurement of these properties in fields with vegetable crop production. It is hoped that these calibration models will enable successful as accurate measurement of P and K in particular, as these are essential properties for plant growth and development, and essential to determine the P and K fertiliser recommendations. It is also essential to include not only pH, OC, TN and MC in the delineation of fertility maps, as done in the current work, but to account for other soil properties in the analyses.
2. To improve nitrogen fertiliser recommendations, larger N rate differences amongst fertiliser application treatments have to be implemented, i.e. the percentage of application below/above RB209 (Defra, 2010) has to be higher (e.g. ±40%), but always having in mind environmental risks (in case of higher per cent of application rates) and compliance with legislation (EU directives).
3. There is a need to provide the scientific underpinnings for applying the forthcoming VR2 based on the on-line vis-NIR technologies and data fusion approach, for particular crop types.
4. There is a need to investigate and prove the successful use of VR2 approach as compared particularly to UR (current practice in vegetable crop production in the UK), from crop response point of view and input cost. This is essential to provide farmers and advisors valuable background information in deciding whether an investment in PA will improve farm profitability. To do this, it is important to calculate net benefits, i.e. net gain or loss for each of the three application treatments (UR, VR1 and VR2). In this respect it is necessary to move a step forward and calculate yield (expected Brassica yield) for the field in

trays/ha and extra costs for using VR technologies. The subsidy and tax imposed on the leaching of nitrogen fertiliser application has to be also taken into account.

5. Other marketable yield quality attributes such as trimming, colour, riceyness, freshness, rot, pest and disease, aroma, taste, or texture might need to be considered in forthcoming studies, since they are indicators of healthy plants. If one of these quality attributes does not fit the market standards the produce will be rejected out of the system.

REFERENCES

Adamchuk, V. I., Hummel, J. W., Morgan, M. T. and Upadhyaya, S. K. (2004), "On-the-go soil sensors for precision agriculture", *Computers and Electronics in Agriculture,* vol. 44, no. 1, pp. 71-91.

Aggelopoulou, K., Pateras, D., Fountas, S., Gemtos, T. and Nanos, G. (2007), "Soil spatial variability in small Greek apple orchards", *Precision Agriculture'07,* vol. 7, pp. 61.

AHDB DairyCo (2015)*, UK fertiliser prices*, available at: www.dairyco.org.uk (accessed 11/14).

Alchanatis, V., Cohen, Y., Cohen, S., Moller, M., Meron, M., Tsipris, J., Orlov, V., Naor, A. and Charit, Z. (2006), "Fusion of IR and multispectral images in the visible range for empirical and model based mapping of crop water status", *Proceeding ASABE Annual International Meeting,* pp. 9.

Alchanatis, V., Safren, O., Levi, O., Ostrovsky, V. and Stafford, J. (2007), "Apple yield mapping using hyperspectral machine vision.", *Precision agriculture'07. Papers presented at the 6th European Conference on Precision Agriculture, Skiathos, Greece, 3-6 June, 2007.* Wageningen Academic Publishers, pp. 555.

Arnó, J., Bordes, X., Ribes-Dasi, M., Blanco, R., Rosell, J., Esteve, J. and Stafford, J. (2005), "Obtaining grape yield maps and analysis of within-field variability in Raimat (Spain).", *Precision agriculture'05. Papers presented at the 5th European Conference on Precision Agriculture, Uppsala, Sweden.* Wageningen Academic Publishers, pp. 899.

Ballesteros, R., Ortega, J., Hernández, D. and Moreno, M. (2014), "Applications of georeferenced high-resolution images obtained with unmanned aerial vehicles. Part II: application to maize and onion crops of a semi-arid region in Spain", *Precision Agriculture,* vol. 15, no. 6, pp. 593-614.

Balsari, P., Doruchowski, G., Marucco, P., Tamagnone, M., Van De Zande, J. and Wenneker, M. (2008), "A system for adjusting the spray application to the target characteristics", *Agr.Eng.Int.CIGR Ejournal,* vol. 10, pp. 1-11.

Bonilla, I., d Toda, F. M. and Martínez-Casasnovas, J. (2013), "Grape quality assessment by airborne remote sensing over three years", in *Precision agriculture'13,* Springer, , pp. 611-615.

British Standard, BS 7755 Section 3.1, (1994), *Determination of dry matter and water content on a mass basis by a gravimetric method*.

British Standard, BS 7755 Section 3.12., (1996), *Determination of the potential cation exchange capacity and exchangeable cations using barium chloride buffered at pH = 8.1.*

British Standard, BS 7755 Section 3.8, (1995), *Determination of organic and total carbon after dry combustion (elementary analysis)*.

Bulanon, D., Burks, T. and Alchanatis, V. (2008), "Study on temporal variation in citrus canopy using thermal imaging for citrus fruit detection", *Biosystems Engineering,* vol. 101, no. 2, pp. 161-171.

Bulanon, D., Kataoka, T., Ota, Y. and Hiroma, T. (2002), "AE—automation and emerging technologies: A segmentation algorithm for the automatic recognition of Fuji apples at harvest", *Biosystems Engineering,* vol. 83, no. 4, pp. 405-412.

Christy, C. D. (2008), "Real-time measurement of soil attributes using on-the-go near infrared reflectance spectroscopy", *Computers and Electronics in Agriculture,* vol. 61, no. 1, pp. 10-19.

De Benedetto, D., Castrignano, A., Diacono, M., Rinaldi, M., Ruggieri, S. and Tamborrino, R. (2013), "Field partition by proximal and remote sensing data fusion", *Biosystems Engineering,* vol. 114, no. 4, pp. 372-383.

Defra, A. (2010), "Fertiliser manual RB209", *London, UK: Department for Environment, Food and Rural Affairs,* .

Dobermann, A. and Ping, J. (2004), "Geostatistical integration of yield monitor data and remote sensing improves yield maps", *Agronomy Journal,* vol. 96, no. 1, pp. 285-297.

Dunn, B., Batten, G., Beecher, H. and Ciavarella, S. (2002), "The potential of near-infrared reflectance spectroscopy for soil analysis—a case study from the Riverine Plain of south-eastern Australia", *Animal Production Science,* vol. 42, no. 5, pp. 607-614.

Faithfull, N. T. (2002), *Methods in agricultural chemical analysis: a practical handbook,* Wallingford : CABI Publishing, 2002.

Fang, L. (2011), *On-line visible and near infrared (vis.NIR) measurement of total nitrogen in vegetable crop production fields* (MSc thesis), Cranfield University, UK.

Fernández-Pacheco, D. G., Escarabajal-Henarejos, D., Ruiz-Canales, A., Conesa, J. and Molina-Martínez, J. M. (2014), "A digital image-processing-based method for determining the crop coefficient of lettuce crops in the southeast of Spain", *Biosystems Engineering,* vol. 117, no. 0, pp. 23-34.

Gil, E., Escolà, A., Rosell, J., Planas, S. and Val, L. (2007), "Variable rate application of plant protection products in vineyard using ultrasonic sensors", *Crop Protection,* vol. 26, no. 8, pp. 1287-1297.

Giles, D., Delwiche, M. and Dodd, R. (1989), "Sprayer control by sensing orchard crop characteristics: Orchard architecture and spray liquid savings", *Journal of Agricultural Engineering Research,* vol. 43, pp. 271-289.

Guerrero, C., Stenberg, B., Wetterlind, J., Viscarra Rossel, R., Maestre, F., Mouazen, A., Zornoza, R., Ruiz-Sinoga, J. and Kuang, B. (2014), "Assessment of soil organic carbon at local scale with spiked NIR calibrations: effects of selection and extra-weighting on the spiking subset", *European Journal of Soil Science,* vol. 65, no. 2, pp. 248-263.

Halcro, G., Corstanje, R. and Mouazen, A. (2013), "Site-specific land management of cereal crops based on management zone delineation by proximal soil sensing", in *Precision agriculture'13,* Springer, , pp. 475-482.

Idso, S., Jackson, R., Pinter Jr, P., Reginato, R. and Hatfield, J. (1981), "Normalizing the stress-degree-day parameter for environmental variability", *Agricultural Meteorology,* vol. 24, pp. 45-55.

Jahn, O. L. (1979), "Penetration of Photosynthetically Active Radiation as a Measurement of Canopy Density 01 Citrus Trees", *J.Amer.Soc.Hort.Sci,* vol. 104, no. 4, pp. 557-560.

Jiménez-Bello, M., Royuela, A., Manzano, J., Zarco-Tejada, P. and Intrigliolo, D. (2013), "Assessment of drip irrigation sub-units using airborne thermal imagery acquired with an Unmanned Aerial Vehicle (UAV)", in *Precision agriculture'13,* Springer, , pp. 705-711.

Kane, K. and Lee, W. S. (2007), "Multispectral imaging for in-field green citrus identification", *American Society of Agricultural and Biological Engineers,* , no. 073025.

Kaukoranta, T., Murto, J., Takala, J. and Tahvonen, R. (2005), "Detection of water deficit in greenhouse cucumber by infrared thermography and reference surfaces", *Scientia Horticulturae,* vol. 106, no. 4, pp. 447-463.

Koller, M. and Upadhyaya, S. (2005a), "Prediction of processing tomato yield using a crop growth model and remotely sensed aerial images", *Transactions of the ASAE,* vol. 48, no. 6, pp. 2335-2341.

Koller, M. and Upadhyaya, S. (2005b), "Relationship between modified normalized difference vegetation index and leaf area index for processing tomatoes", *Applied Engineering in Agriculture,* .

Kuang, B. and Mouazen, A. (2011a), "On-the-go measurement of key soil properties in European farms", *2nd Global Workshop on Proximal Soil Sensing, 15 - 19 May, 2011, Montreal - Canada,* .

Kuang, B. and Mouazen, A. (2011b), "On-the-go soil sensing: results of field measurement in a UK farm", *The 8th European COnference of Precision Agriculture (ECPA), 11-14 July, 2011, Prague, Czech Republic,* , pp. 585-591.

Kuang, B. and Mouazen, A. (2011c), "Calibration of visible and near infrared spectroscopy for soil analysis at the field scale on three European farms", *European Journal of Soil Science,* vol. 62, no. 4, pp. 629-636.

Kuang, B., Mahmood, H. S., Quraishi, M. Z., Hoogmoed, W. B., Mouazen, A. M. and van Henten, E. J. (2012), "4 Sensing Soil Properties in the Laboratory, In Situ, and On-Line: A Review", *Advances in Agronomy,* vol. 114, no. 1, pp. 155-223.

Kuang, B. and Mouazen, A. M. (2012), "Influence of the number of samples on prediction error of visible and near infrared spectroscopy of selected soil properties at the farm scale", *European Journal of Soil Science,* vol. 63, no. 3, pp. 421-429.

Kuang, B. and Mouazen, A. M. (2013), "Effect of spiking strategy and ratio on calibration of on-line visible and near infrared soil sensor for measurement in European farms", *Soil and Tillage Research,* vol. 128, no. 0, pp. 125-136.

Lee, W. and Slaughter, D. (2004), "Recognition of partially occluded plant leaves using a modified watershed algorithm", *TRANSACTIONS-AMERICAN SOCIETY OF AGRICULTURAL ENGINEERS,* vol. 47, no. 4, pp. 1269-1280.

Lee, W. S., Alchanatis, V., Yang, C., Hirafuji, M., Moshou, D. and Li, C. (2010), "Sensing technologies for precision specialty crop production", *Computers and Electronics in Agriculture,* vol. 74, no. 1, pp. 2-33.

Leinonen, I. and Jones, H. G. (2004), "Combining thermal and visible imagery for estimating canopy temperature and identifying plant stress", *Journal of experimental botany,* vol. 55, no. 401, pp. 1423-1431.

López, A., Molina-Aiz, F. D., Valera, D. L. and Peña, A. (2012), "Determining the emissivity of the leaves of nine horticultural crops by means of infrared thermography", *Scientia Horticulturae,* vol. 137, no. 0, pp. 49-58.

López Riquelme, J., Soto, F., Suardíaz, J., Sánchez, P., Iborra, A. and Vera, J. (2009), "Wireless sensor networks for precision horticulture in Southern Spain", *Computers and Electronics in Agriculture,* vol. 68, no. 1, pp. 25-35.

Maguire, S., Earl, R., Smith, D. F., Cripsey, P., Godwin, R. J., Stafford, J. and Werner, A. (2003), "Technology for variable rate precision drilling of onions", *Precision agriculture. Wageningen Academic Publishers, Wageningen,* , pp. 373-378.

Mahmood, H., Hoogmoed, W. and Van Henten, E. (2011), "Estimating soil properties with a proximal gamma ray spectrometer using windows and full-spectrum analysis methods", *Proceedings of the Second Global Workshop on Proximal Soil Sensing, Montreal, Canada,* pp. 15.

Maleki, M. R., Ramon, H., De Baerdemaeker, J. and Mouazen, A. M. (2008), "A study on the time response of a soil sensor-based variable rate granular fertiliser applicator", *Biosystems engineering,* vol. 100, no. 2, pp. 160-166.

Marín-González, O., Kuang, B., Quraishi, M. Z., Munóz-García, M. Á. and Mouazen, A. M. (2013), "On-line measurement of soil properties without direct spectral response in near infrared spectral range", *Soil and Tillage Research,* vol. 132, pp. 21-29.

Martens, H. and Naes, T. (1989), *Multivariate calibration,* second ed, John Wiley & Sons, Chichester, UK.

Matese, A., Capraro, F., Primicerio, J., Gualato, G., Di Gennaro, S. and Agati, G. (2013), "Mapping of vine vigor by UAV and anthocyanin content by a non-destructive fluorescence technique", in *Precision agriculture'13,* Springer, , pp. 201-208.

Moller, M., Alchanatis, V., Cohen, Y., Meron, M., Tsipris, J., Naor, A., Ostrovsky, V., Sprintsin, M. and Cohen, S. (2007), "Use of thermal and visible imagery for estimating crop water status of irrigated grapevine", *Journal of experimental botany,* vol. 58, no. 4, pp. 827-838.

Moltó, E., Martın, B. and Gutiérrez, A. (2001), "PM—Power and Machinery: Pesticide Loss Reduction by Automatic Adaptation of Spraying on Globular Trees", *Journal of Agricultural Engineering Research,* vol. 78, no. 1, pp. 35-41.

Monaghan, J. M., Daccache, A., Vickers, L. H., Hess, T. M., Weatherhead, E. K., Grove, I. G. and Knox, J. W. (2013), "More ‘crop per drop’: constraints and opportunities for precision irrigation in European agriculture", *Journal of the science of food and agriculture,* vol. 93, no. 5, pp. 977-980.

Morgan, M. and Ess, D. (1997), "The precision-farming guide for agriculturists", *Deere and Company*.

Mouazen, A. M. and Ramon, H. (2006), "Development of on-line measurement system of bulk density based on on-line measured draught, depth and soil moisture content", *Soil and Tillage Research,* vol. 86, no. 2, pp. 218-229.

Mouazen, A. M., Alhwaimel, S. A., Kuang, B. and Waine, T. (2014), "Multiple on-line soil sensors and data fusion approach for delineation of water holding capacity zones for site specific irrigation", *Soil and Tillage Research,* vol. 143, pp. 95-105.

Mouazen, A. (2006). “Soil Survey Device. International publication published under the patent cooperation treaty (PCT)”.*World Intellectual Property Organization, International Bureau*. International Publication Number: WO2006/015463; PCT/BE2005/000129; IPC: G01N21/00; G01N21/00.

Mouazen, A., Alhwaimel, S., Kuang, B. and Waine, T. (2013), "Fusion of data from multiple soil sensors for the delineation of water holding capacity zones", in *Precision agriculture’13,* Springer, pp. 745-751.

Mouazen, A., De Baerdemaeker, J. and Ramon, H. (2006), "Effect of wavelength range on the measurement accuracy of some selected soil constituents using visual-near infrared spectroscopy", *Journal of near infrared spectroscopy,* vol. 14, no. 3, pp. 189-199.

Mouazen, A. M., De Baerdemaeker, J. and Ramon, H. (2005), "Towards development of on-line soil moisture content sensor using a fibre-type NIR spectrophotometer", *Soil and Tillage Research,* vol. 80, no. 1-2, pp. 171-183.

Mouazen, A. M., Maleki, M. R., Cockx, L., Van Meirvenne, M., Van Holm, L. H. J., Merckx, R., De Baerdemaeker, J. and Ramon, H. (2009), "Optimum three-point linkage set up for improving the quality of soil spectra and the accuracy of soil phosphorus measured using an on-line visible and near infrared sensor", *Soil and Tillage Research,* vol. 103, no. 1, pp. 144-152.

Mouazen, A. M., Maleki, M. R., De Baerdemaeker, J. and Ramon, H. (2007), "On-line measurement of some selected soil properties using a VIS–NIR sensor", *Soil and Tillage Research,* vol. 93, no. 1, pp. 13-27.

Nicolaï, B. M., Beullens, K., Bobelyn, E., Peirs, A., Saeys, W., Theron, K. I. and Lammertyn, J. (2007), "Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review", *Postharvest Biology and Technology,* vol. 46, no. 2, pp. 99-118.

Oki, K., Mitsuishi, S., Ito, T. and Mizoguchi, M. (2009), "An agricultural monitoring system based on the use of remotely sensed imagery and field server web camera data", *GIScience & Remote Sensing,* vol. 46, no. 3, pp. 305-314.

Olsen, S. R. (1954), "Estimation of available phosphorus in soils by extraction with sodium bicarbonate".

Ortega, R., Esser, A., Inostroza, A., Jara, L. and Stafford, J. (2007), "Tomato yield and quality prediction by using a calibrated, satellite-based, green vegetation index (GVI).", *Precision agriculture'07. Papers presented at the 6th European Conference on Precision Agriculture, Skiathos, Greece, 3-6 June, 2007.* Wageningen Academic Publishers, pp. 573.

Paoli, J., Tisseyre, B., Strauss, O., Roger, J., Guillaume, S. and Stafford, J. (2005), "Combination of heterogeneous data sets in precision viticulture.", *Precision agriculture'05. Papers presented at the 5th European Conference on Precision Agriculture, Uppsala, Sweden.* Wageningen Academic Publishers, pp. 915.

Pfenning, J., Graeff, S., Claupein, W., Liebig, H. and Stafford, J. (2007), "Use of reflectance measurements to determine the N demand of broccoli plants (Brassica oleracea convar. botrytis var. italica).", *Precision agriculture'07.*

Papers presented at the 6th European Conference on Precision Agriculture, Skiathos, Greece, 3-6 June, 2007. Wageningen Academic Publishers, pp. 657.

Planas, S., Camp, F., Solanelles, F., Sanz, R. and Rosell-Polo, J. (2013), "Advances in pesticide dose adjustment in tree crops", in *Precision agriculture'13,* Springer, , pp. 533-539.

Quraishi, M. Z. and Mouazen, A. M. (2013), "Calibration of an on-line sensor for measurement of topsoil bulk density in all soil textures", *Soil and Tillage Research,* vol. 126, pp. 219-228.

Rabatel, G. and Guizard, C. (2007), "Grape berry calibration by computer vision using elliptical model fitting", *ECPA 2007, 6th European Conference on Precision Agriculture*.

Rey, C., Martín, M., Lobo, A., Luna, I., Diago, M., Millan, B. and Tardáguila, J. (2013), "Multispectral imagery acquired from a UAV to assess the spatial variability of a Tempranillo vineyard", in *Precision agriculture'13,* Springer, pp. 617-624.

Ribeiro da Luz, B. and Crowley, J. K. (2007), "Spectral reflectance and emissivity features of broad leaf plants: Prospects for remote sensing in the thermal infrared (8.0–14.0 μm)", *Remote Sensing of Environment,* vol. 109, no. 4, pp. 393-405.

Rinaldi, M., Llorens, J. and Gil, E. (2013), "Electronic characterization of the phenological stages of grapevine using a LIDAR sensor", in *Precision agriculture'13,* Springer, pp. 603-609.

Roberts, R. K., English, B. C. and Mahajanashetti, S. (2000), "Evaluating the returns to variable rate nitrogen application", *Journal of Agricultural and Applied Economics,* vol. 32, no. 1, pp. 133-144.

Rossel, R. V. and McBratney, A. (1998), "Soil chemical analytical accuracy and costs: implications from precision agriculture", *Animal Production Science,* vol. 38, no. 7, pp. 765-775.

Rud, R., Cohen, Y., Alchanatis, V., Dar, Z., Levi, A., Brikman, R., Shenderey, C., Heuer, B., Markovits, T. and Mulla, D. (2013), "The potential of CWSI based on thermal imagery for in-season irrigation management in potato fields", in *Precision agriculture’13,* Springer, , pp. 721-727.

Ruiz-Altisent, M., Ruiz-Garcia, L., Moreda, G. P., Lu, R., Hernandez-Sanchez, N., Correa, E. C., Diezma, B., Nicolaï, B. and García-Ramos, J. (2010), "Sensors for product characterization and quality of specialty crops—A review", *Computers and Electronics in Agriculture,* vol. 74, no. 2, pp. 176-194.

Safren, O., Alchanatis, V., Ostrovsky, V. and Levi, O. (2007), "Detection of green apples in hyperspectral images of apple-tree foliage using machine vision", *Transactions of the ASABE,* vol. 50, no. 6, pp. 2303-2313.

Schumann, A., Miller, W., Zaman, Q., Hostler, K., Buchanon, S. and Cugati, S. (2006), "Variable rate granular fertilization of citrus groves: Spreader performance with single-tree prescription zones", *Applied Engineering in Agriculture,* vol. 22, no. 1, pp. 19.

Selbeck, J. and Pforte, F. (2013), "Automated determination of plum tree canopy cover with two different measurement techniques", in *Precision agriculture’13,* Springer, pp. 667-673.

Senay, G., Ward, A., Lyon, J., Fausey, N. and Nokes, S. (1998), "Manipulation of high spatial resolution aircraft remote sensing data for use in site-specific farming", *Transactions of the ASAE,* vol. 41, no. 2, pp. 489-495.

Smart, R., Dick, J. K., Gravett, I. M. and Fisher, B. (1990), "Canopy management to improve grape yield and wine quality-principles and practices", *S.Afr.J.Enol.Vitic,* vol. 11, no. 1, pp. 3-17.

Solanelles, F., Escolà, A., Planas, S., Rosell, J., Camp, F. and Gràcia, F. (2006), "An electronic control system for pesticide application proportional to the canopy width of tree crops", *Biosystems engineering,* vol. 95, no. 4, pp. 473-481.

Southgate, D. (2009), "Population growth, increases in agricultural production and trends in food prices", *The Electronic Journal of Sustainable Development,* vol. 1, no. 3, pp. 419-428.

Stafford, J. V. (2000), "Implementing Precision Agriculture in the 21st Century", *Journal of Agricultural Engineering Research,* vol. 76, no. 3, pp. 267-275.

Stajnko, D., Lakota, M. and Hočevar, M. (2004), "Estimation of number and diameter of apple fruits in an orchard during the growing season by thermal imaging", *Computers and Electronics in Agriculture,* vol. 42, no. 1, pp. 31-42.

Stenberg, B., Viscarra Rossel, R. A., Mouazen, A. M. and Wetterlind, J. (2010), "Chapter Five-Visible and Near Infrared Spectroscopy in Soil Science", *Advances in Agronomy,* vol. 107, pp. 163-215.

Sudduth, K., Hummel, J., Birrell, S., Pierce, F. and Sadler, E. (1997), "Sensors for site-specific management.", *The state of site specific management for agriculture.,* pp. 183-110.

Tagarakis, A., Liakos, V., Chatzinikos, T., Koundouras, S., Fountas, S. and Gemtos, T. (2013), "Using laser scanner to map pruning wood in vineyards", in *Precision agriculture'13,* Springer, pp. 633-639.

Taylor, J. A., McBratney, A., Viscarra Rossel, R., Minasny, B., Taylor, H., Whelan, B. and Short, M. (2006), "Development of a multi-sensor platform for proximal soil sensing", *18th World Congress of Soil Science July,* pp. 9.

Taylor, J., Tisseyre, B., Bramley, R., Reid, A. and Stafford, J. (2005), "A comparison of the spatial variability of vineyard yield in European and Australian production systems.", *Precision agriculture'05. Papers presented at the 5th European Conference on Precision Agriculture, Uppsala, Sweden.* Wageningen Academic Publishers, pp. 907.

Thomasson, J., Sui, R., Cox, M. and Al-Rajehy, A. (2001), "Soil reflectance sensing for determining soil properties in precision agriculture.", *Transactions of the ASAE,* vol. 44, no. 6, pp. 1445-1453.

Todd, S., Hoffer, R. and Milchunas, D. (1998), "Biomass estimation on grazed and ungrazed rangelands using spectral indices", *International Journal of Remote Sensing,* vol. 19, no. 3, pp. 427-438.

U.S. Geological Survey (2013)*, Using the USGS Landsat 8 Product*, available at: http://landsat.usgs.gov (accessed 04/17).

Urretavizcaya, I., Santesteban, L., Guillaume, S., Royo, J., Miranda, C. and Tisseyre, B. (2013), "Prediction of spatial variability of water status in a rain fed vineyard in Spain", in *Precision agriculture'13,* Springer, , pp. 459-465.

Usha, K. and Singh, B. (2013), "Potential applications of remote sensing in horticulture—A review", *Scientia Horticulturae,* vol. 153, pp. 71-83.

van Evert, F., van der Schans, D., van Geel, W., Malda, J. and Vona, V. (2013), "From theory to practice: using canopy reflectance to determine sidedress N rate in potatoes", in *Precision agriculture'13,* Springer, , pp. 119-127.

Viscarra Rossel, R. A., Walvoort, D. J. J., McBratney, A. B., Janik, L. J. and Skjemstad, J. O. (2006), "Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties", *Geoderma,* vol. 131, no. 1–2, pp. 59-75.

Vrindts, E., Mouazen, A. M., Reyniers, M., Maertens, K., Maleki, M. R., Ramon, H. and De Baerdemaeker, J. (2005), "Management Zones based on Correlation between Soil Compaction, Yield and Crop Data", *Biosystems Engineering,* vol. 92, no. 4, pp. 419-428.

Wachs, J., Stern, H., Burks, T. and Alchanatis, V. (2009), "Multi-modal registration using a combined similarity measure", in *Applications of Soft Computing,* Springer, , pp. 159-168.

Wang, D., Prato, T., Qiu, Z., Kitchen, N. R. and Sudduth, K. A. (2003), "Economic and environmental evaluation of variable rate nitrogen and lime application for claypan soil fields", *Precision Agriculture,* vol. 4, no. 1, pp. 35-52.

Wei, J. and Salyani, M. (2005), "Development of a laser scanner for measuring tree canopy characteristics Phase 2. Foliage density measurement", *Transactions of the ASAE,* vol. 48, no. 4, pp. 1595-1601.

Whelan, B. and McBratney, A. (2000), "The “null hypothesis” of precision agriculture management", *Precision Agriculture,* vol. 2, no. 3, pp. 265-279.

Wood, B. W., Conner, P. J. and Worley, R. E. (2003), "Relationship of alternate bearing intensity in pecan to fruit and canopy characteristics", *HortScience,* vol. 38, no. 3, pp. 361-366.

Yang, C., Liu, T. and Everitt, J. H. (2008), "Estimating cabbage physical parameters using remote sensing technology", *Crop Protection,* vol. 27, no. 1, pp. 25-35.

Yang, H., Kuang, B. and Mouazen, A. M. (2011), "In Situ Determination of Growing Stages and Harvest Time of Tomato (Lycopersicon esculentum) Fruits Using Fiber-Optic Visible–Near-Infrared (Vis-NIR) Spectroscopy", *Applied Spectroscopy,* vol. 65, no. 8, pp. 931-938.

Ye, X., Sakai, K., Asada, S. and Sasao, A. (2008), "Inter-relationships between canopy features and fruit yield in citrus as detected by airborne multispectral imagery", *Transactions of the ASABE,* vol. 51, no. 2, pp. 739-751.

Ye, X., Sakai, K., Manago, M., Asada, S. and Sasao, A. (2007), "Prediction of citrus yield from airborne hyperspectral imagery", *Precision agriculture,* vol. 8, no. 3, pp. 111-125.

Zaman, Q. and Salyani, M. (2004), "Effects of foliage density and ground speed on ultrasonic measurement of citrus tree volume", *Applied Engineering in Agriculture,* vol. 20, no. 2, pp. 173-178.

APPENDICES

Appendix A Development of calibration models

	Samples	Cross-validation set				Prediction set			
	n	Min	Max	Mean	SD	Min	Max	Mean	SD
SC1[a]									
MC (%)	216	11.55	28.61	16.35	2.73	9.25	31.10	13.79	2.91
OC (%)	216	0.96	2.29	1.31	0.21	1.06	1.61	1.23	0.10
pH	216	5.30	8.50	7.51	0.66	5.50	7.20	6.34	0.37
TN (%)	216	0.10	0.22	0.14	0.02	0.13	0.19	0.15	0.01
SC2									
MC (%)	366	9.60	29.08	18.96	4.08	12.70	25.50	18.96	3.62
OC (%)	366	0.96	2.29	1.30	0.19	0.97	1.82	1.30	0.17
pH	366	5.40	8.80	7.87	0.68	5.30	8.60	7.82	0.69
TN (%)	366	0.09	0.22	0.14	0.02	0.10	0.19	0.14	0.02
SC3									
MC (%)	555	5.92	29.08	17.76	4.59	6.74	25.95	18.08	4.11
OC (%)	552	0.96	3.70	1.55	0.45	1.01	2.93	1.57	0.46
pH	506	4.87	8.80	7.60	0.89	5.30	8.70	7.64	0.88
TN (%)	457	0.09	0.39	0.16	0.05	0.10	0.34	0.16	0.05
SC4									
MC (%)	560	5.92	29.08	17.81	4.55	11.80	25.95	18.74	3.60
OC (%)	611	0.96	3.70	1.56	0.44	1.01	2.84	1.52	0.42
pH	576	4.87	8.80	7.59	0.84	5.08	8.70	7.63	0.85
TN (%)	569	0.09	0.39	0.16	0.05	0.08	0.31	0.16	0.05

[a] In SC1 only 216 samples were collected and used as calibration set and 83 fresh soil samples were collected while on-line measurement for the independent validation set.

Table A-1 Sample statistics of calibration set used for partial least squares (PLS) regression cross-validation and prediction set for 2014.

Appendix B Full-data point maps for available phosphorus (P_{avl}), extractable potassium (K_{ex}), extractable calcium (Ca_{ex}), extractable sodium (Na_{ex}), and extractable magnesium (Mg_{ex})

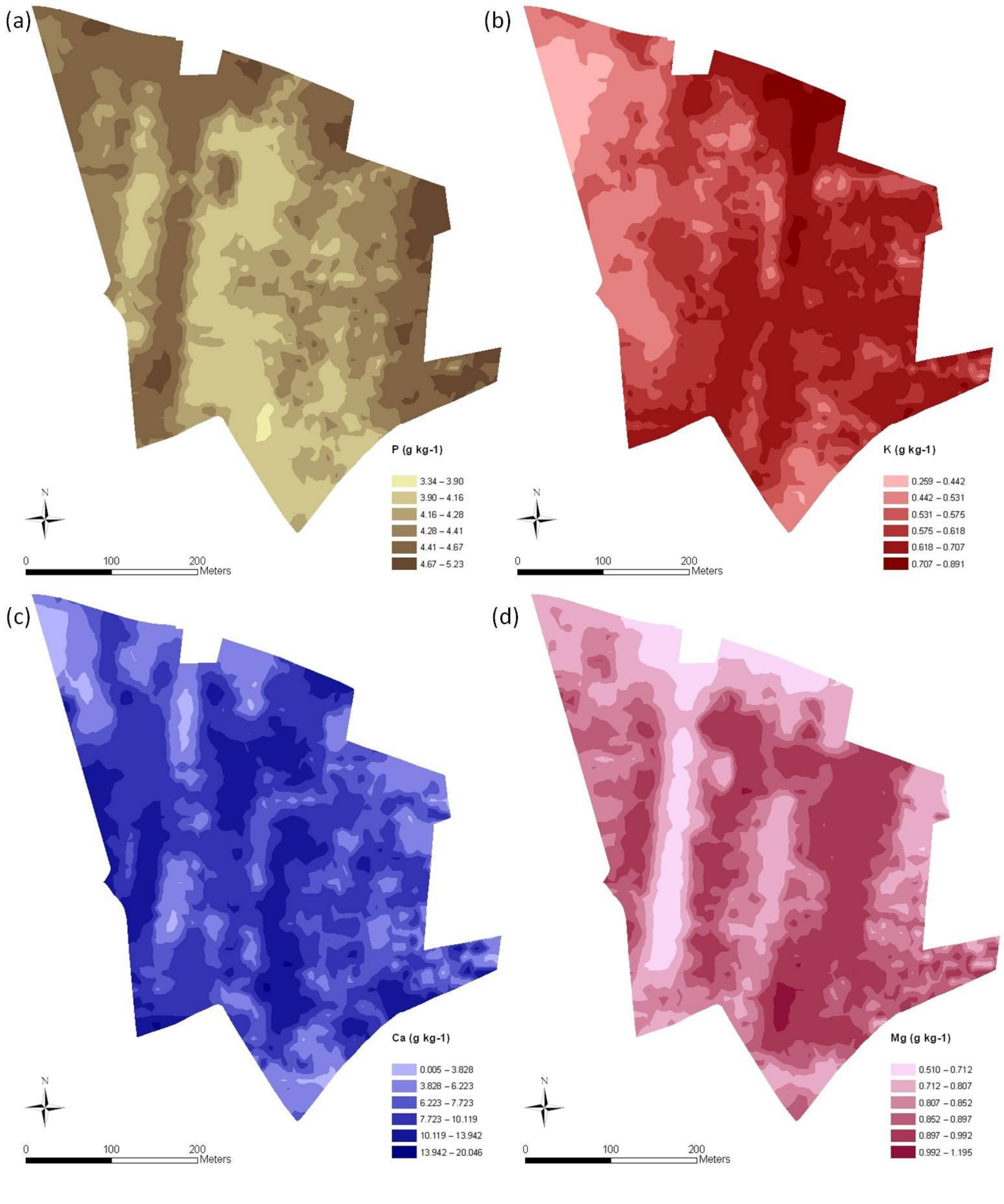


Figure B-1 Full-data point maps of on-line predicted phosphorus (P) (a), potassium (K) (b), calcium (Ca) (c), and magnesium (Mg) (d) in OLD306 field in 2013.

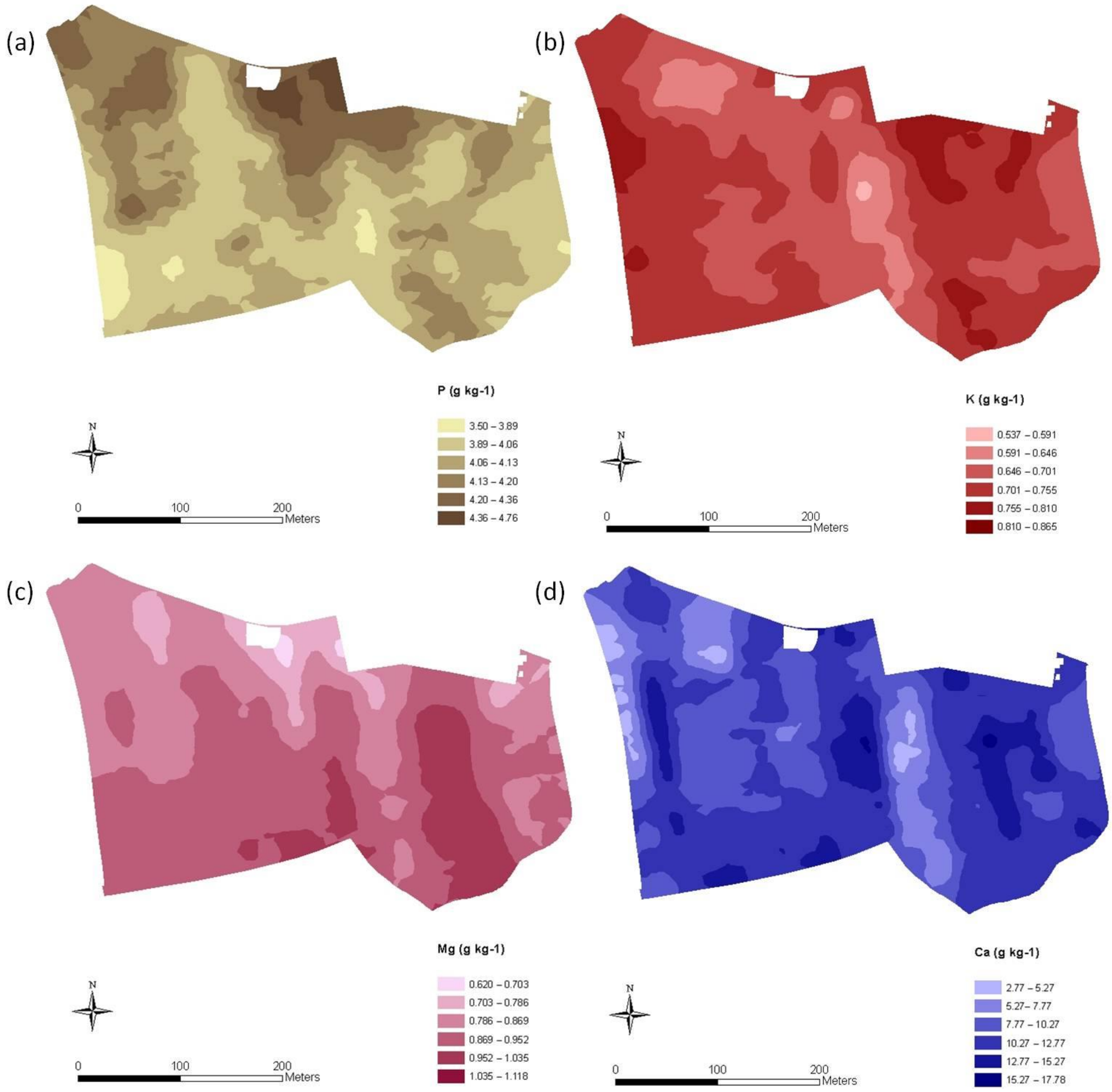


Figure B-2 Full-data point maps of on-line predicted phosphorus (P) (a), potassium (K) (b), magnesium (Mg) (c), and calcium (Ca) (d) in MBHN01 field in 2013.

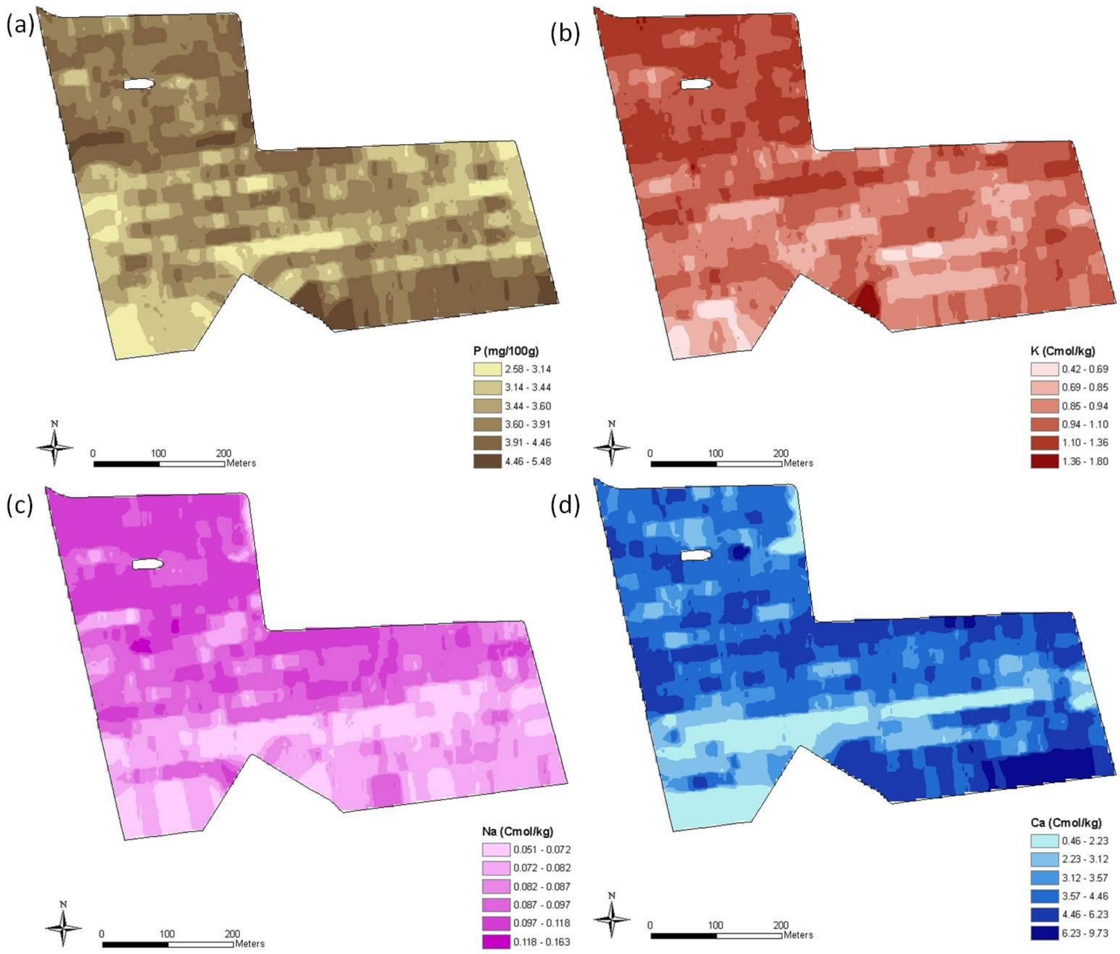


Figure B-3 Full-data point maps of on-line predicted phosphorus (P) (a), potassium (K) (b), sodium (Na) (c), and calcium (Ca) (d) in BWX102 field in 2014.

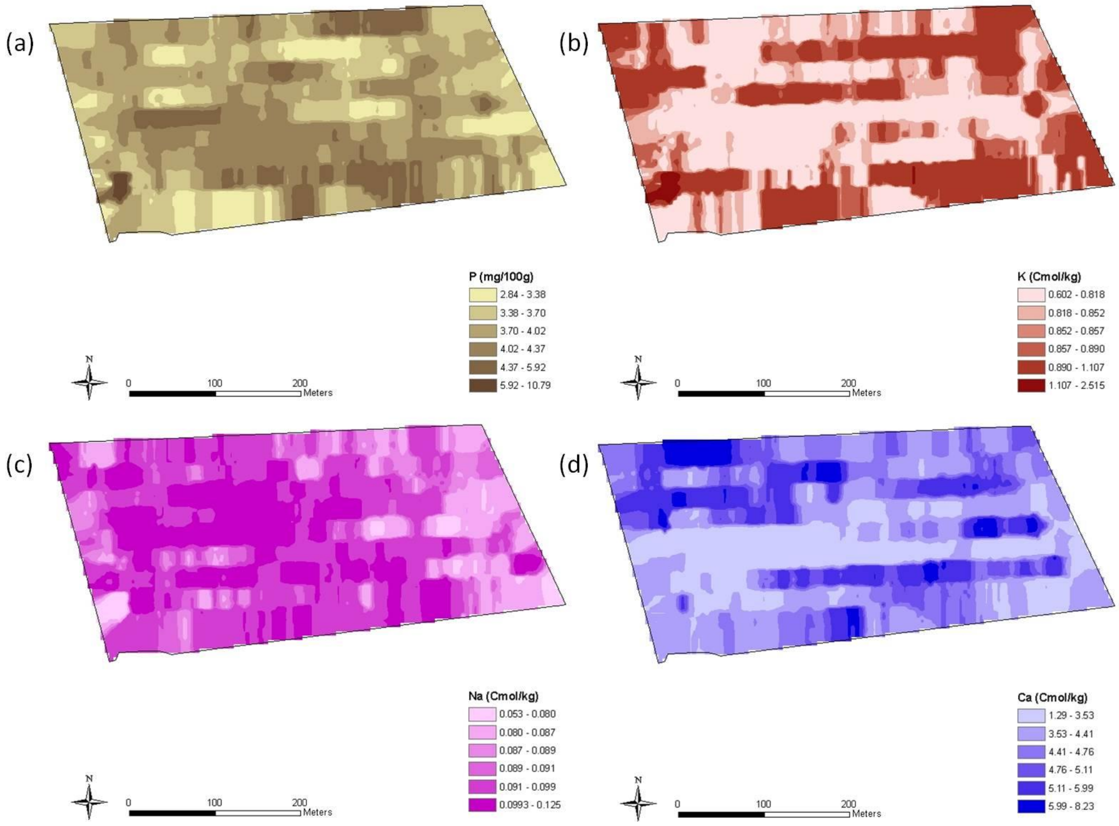


Figure B-4 Full-data point maps of on-line predicted phosphorus (P) (a), potassium (K) (b), sodium (Na) (c), and calcium (Ca) (d) in BWX103 field in 2014.

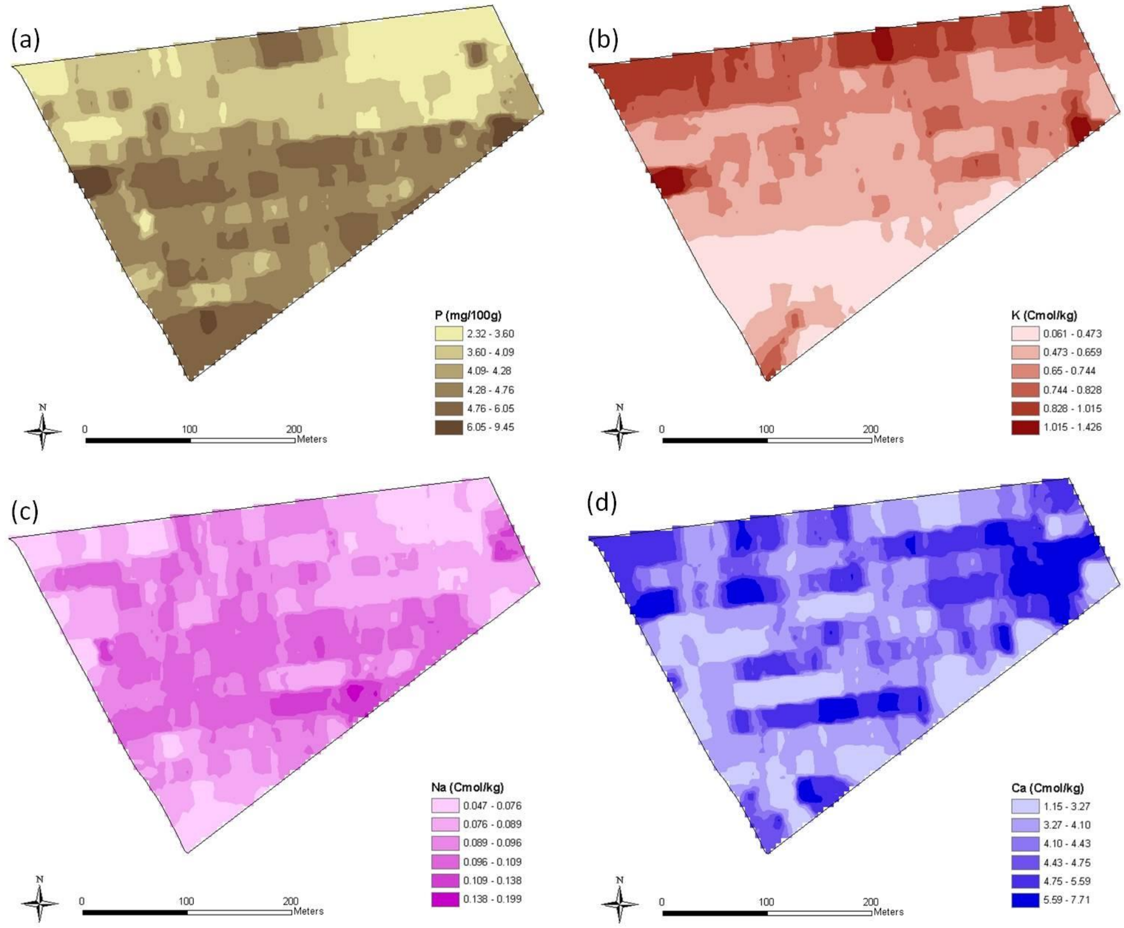


Figure B-5 Full-data point maps of on-line predicted phosphorus (P) (a), potassium (K) (b), sodium (Na) (c), and calcium (Ca) (d) in BWX104 field in 2014.

Appendix C Crop response for 2013 measurement.

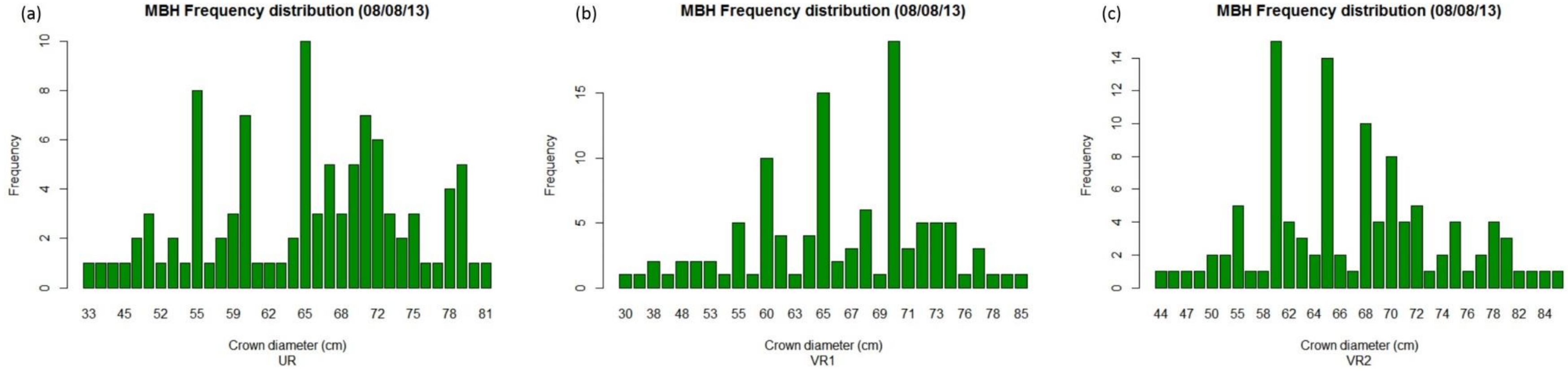


Figure C-1 Frequency distribution of crown diameter in the different treatments in MBHN01: UR (a), VR1 (b), and VR2 (c).

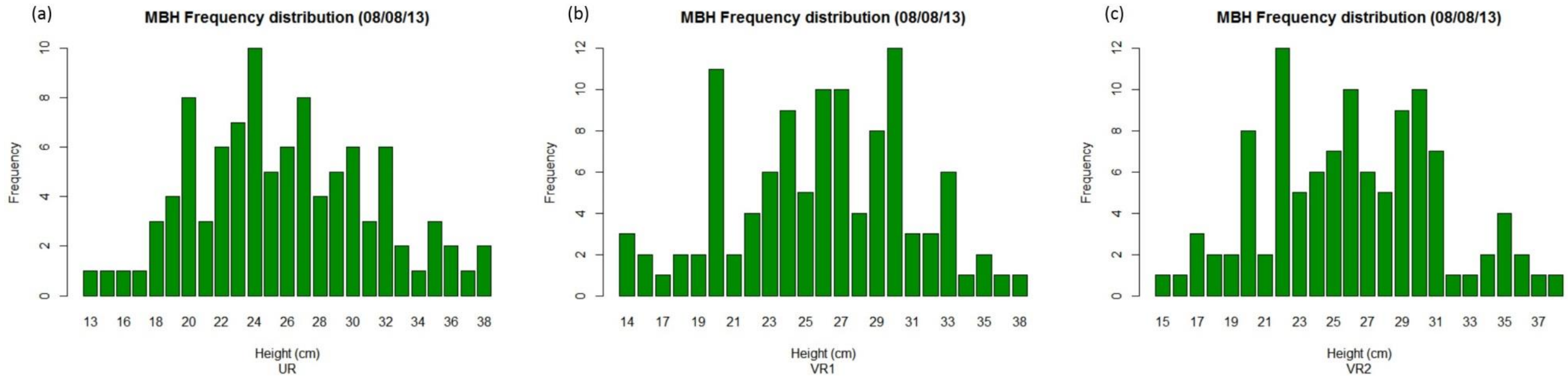


Figure C-2 Frequency distribution of height in the different treatments in MBHN01: UR (a), VR1 (b), and VR2 (c).

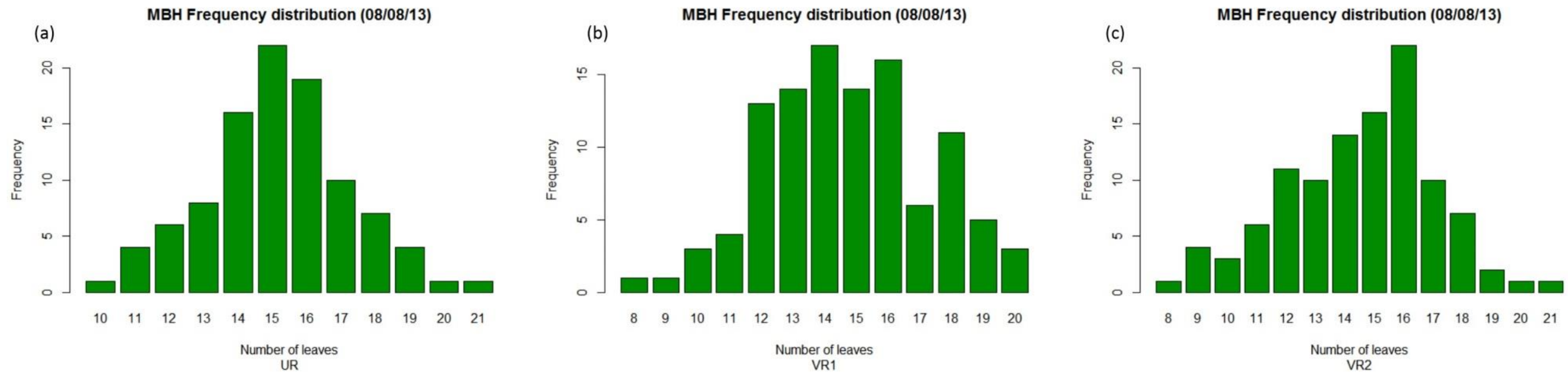


Figure C-3 Frequency distribution of number of leaves in the different treatments in MBHN01: UR (a), VR1 (b), and VR2 (c).

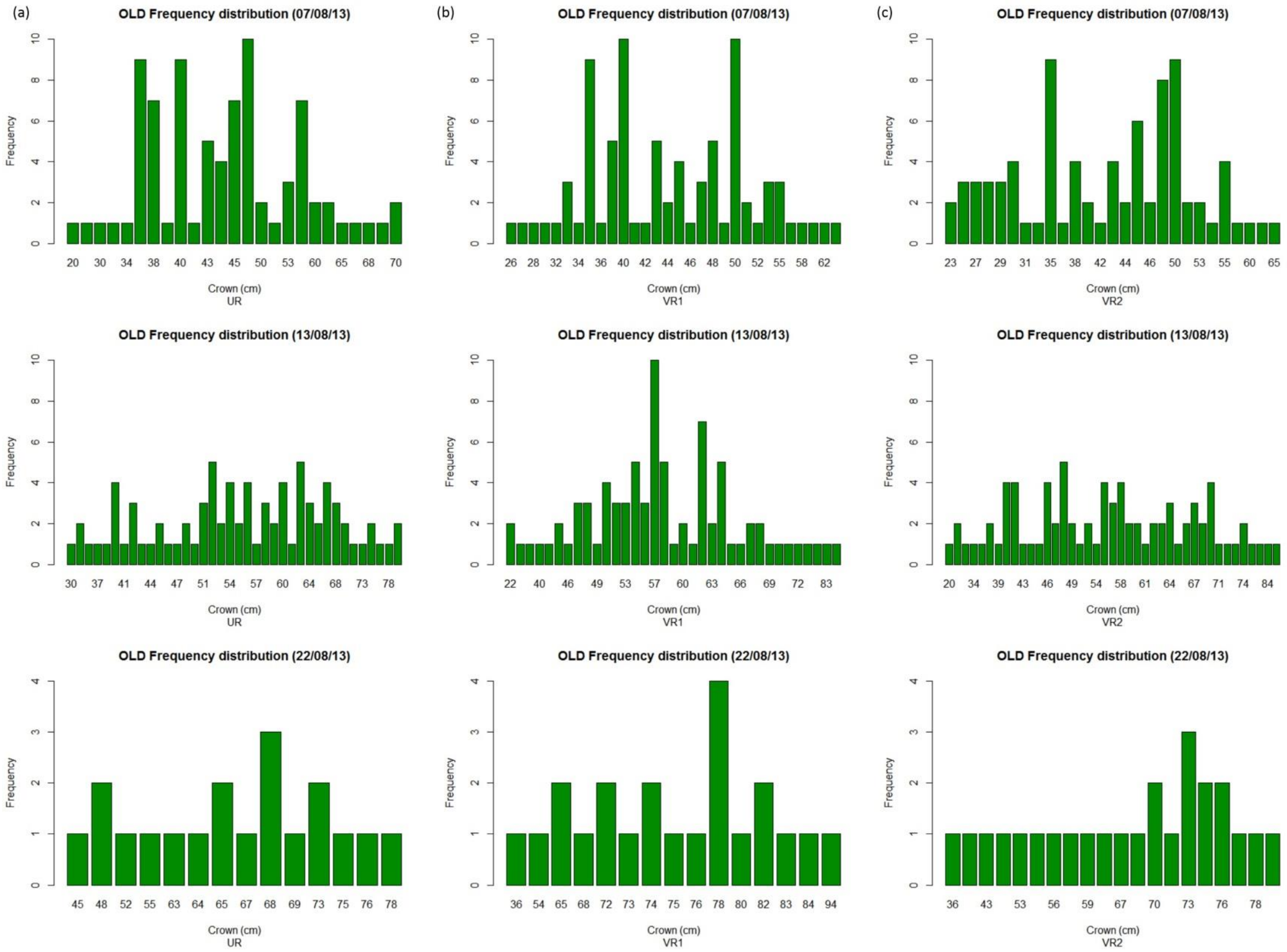


Figure C-4 Frequency distribution of cauliflower crown diameter in the different treatments in OLD306: UR (a), VR1 (b), and VR2 (c). Three measurements were done before harvesting.

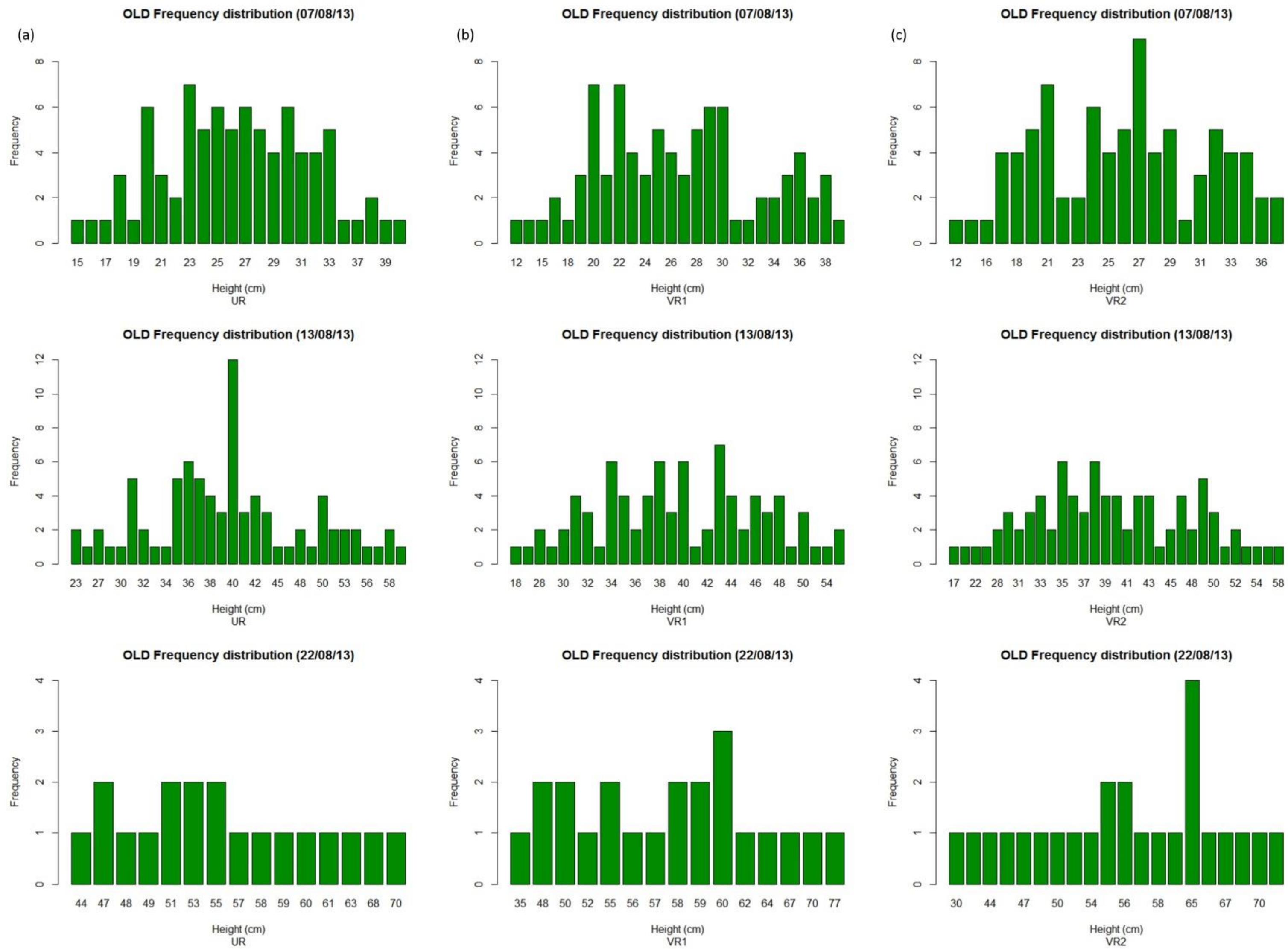


Figure C-5 Frequency distribution of cauliflower height in the different treatments in OLD306: UR (a), VR1 (b), and VR2 (c). Three measurements were done before harvesting.

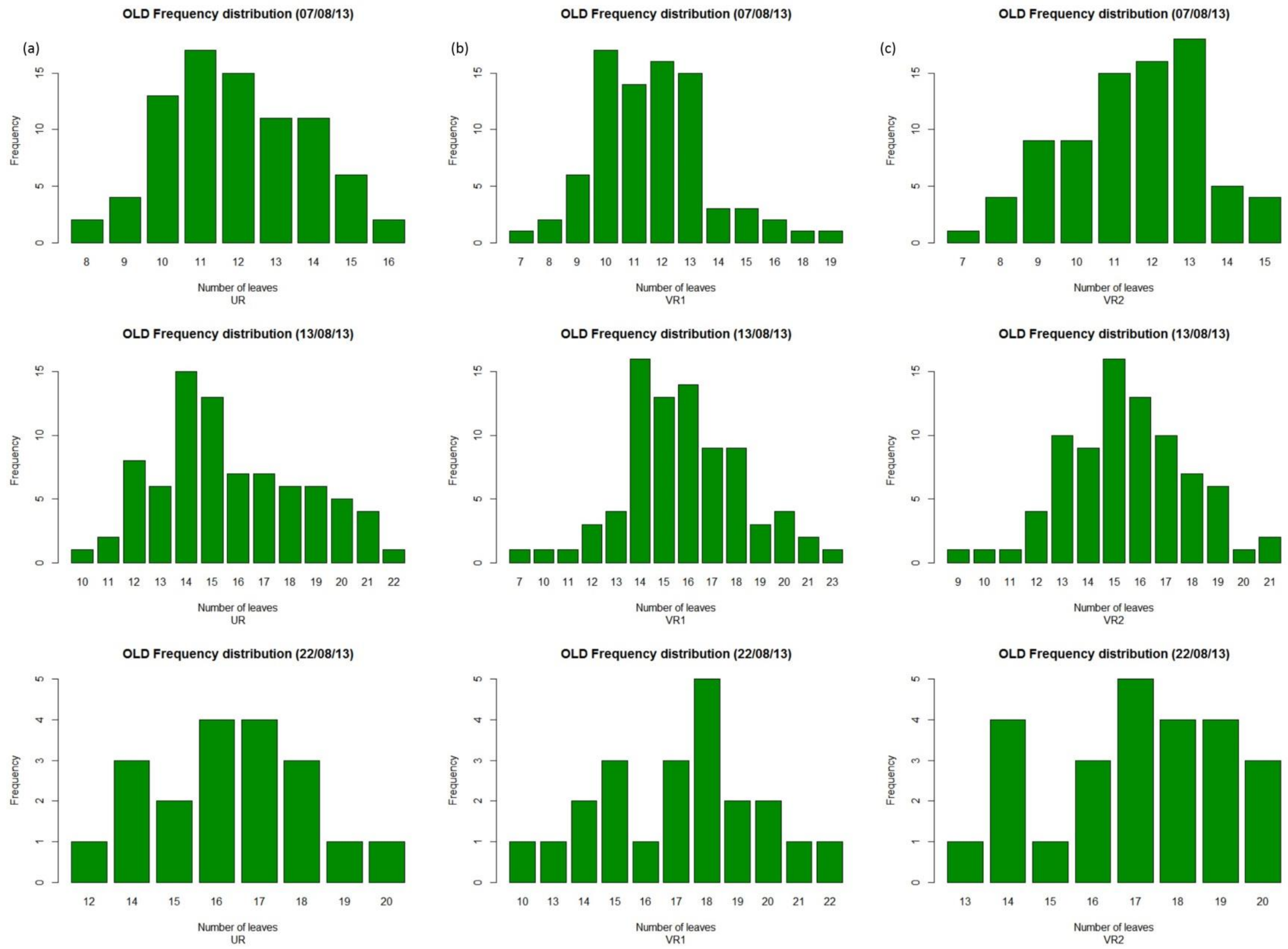


Figure C-6 Frequency distribution of number of leaves in every plant in the different treatments in OLD306: UR (a), VR1 (b), and VR2 (c). Three measurements were done before harvesting.